The Disappearing Index Effect*

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Abstract

The abnormal return associated with a stock being added to the S&P 500 has fallen from an average of 3.4% in the 1980s and 7.6% in the 1990s to 0.8% over the past decade. This has occurred despite a significant increase in the percentage of stock market assets linked to the index. A similar pattern has occurred for index deletions, with large negative abnormal returns on average during the 1980s and 1990s, but only -0.6% between 2010 and 2020. We investigate the drivers of this surprising phenomenon and discuss the implications for market efficiency.

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One of the early and persuasive challenges to the efficient markets hypothesis is the observation that stock prices react to investor demand unrelated to fundamentals. Shleifer (1986) and Harris and Gurel (1986) showed that stocks added to the S&P 500 index experienced abnormal returns of approximately 3 percent around the announcement of the index change. Since then, an extensive literature has documented similar price impact in other stock indexes such as the Russell and the MSCI, as well as many other settings in which investors buy or sell for reasons unrelated to fundamentals, including mutual fund inflows, mechanical reinvestment of dividends, price pressure around mergers, and Treasury auctions.[1]

The initial studies of S&P 500 changes were performed during a time when index investing was nascent. Shleifer (1986) notes that S&P 500 announcement returns were smaller pre-1976 than the 1976-1983 period he focuses on, consistent with more dollars tracking the index leading to more price pressure. Over the past 40 years, driven by inflows into passive mutual funds and ETFs, index tracking has continued to grow at a rapid pace. We estimate that funds that tracking the S&P 500 in the form of mutual funds or ETFs have grown from essentially zero in the 1980s to approximately 7 percent of market capitalization in recent years. Other estimates, based on trading volume (Chinco and Sammon 2022) or sell-side research, suggest even higher levels of investor indexation to the S&P 500 today.

What has happened to the price impact associated with being added to or removed from the S&P 500? A natural starting point would be to assume a demand curve with a constant elasticity, hit by a shock that has been growing in magnitude over time:

$$Price\ Impact_{it} = M \times D_{it} \qquad (1)$$

where $Price\ Impact_{it}$ denotes the percentage change in price, D_{it} refers to the percentage of capitalization of stock i bought upon index addition or sold upon index deletion, and the multiplier M denotes minus 1 over the demand elasticity. Given the rise of indexation, this logic would predict substantially growing price

[1] See e.g., Warther (1995), Mitchell, Pulvino and Stafford (2005), Ben-Rephael, Kandel and Wohl (2010), Lou, Yan and Zhang (2013) and Hartzmark and Solomon (2022).

impact from the 1980s onwards. Conforming to this intuition, we show that the average price impact grew from the 1980s to the 1990s, from an average total return of 3.4% in the 1980s to 7.6% in the 1990s. Surprisingly, however, and consistent with Bennett, Stulz and Wang (2020), we show that the average price impact fell somewhat in the first decade of the 2000s to 5.2%, and then fell to 0.8% in the most recent decade, statistically indistinguishable from zero, even though indexation has continued to tick upwards. A similar pattern has occurred with index deletions. The average effect of being removed from the S&P 500 was -4.6% in the 1980s, -16.6% in the 1990s, -12.3% from 2000-2009, and -0.6% from 2010-2020. Again, the average return in the past decade is not statistically distinguishable from zero.

Why did the S&P 500 index effect seemingly disappear? And if so, can we interpret this change from the lens of market efficiency? We consider four broad classes of explanation:

1) Changing composition of additions and deletions: We quickly rule out that the effects we document are driven by changes in the characteristics of additions and deletions since the 1980s, although such shifts do account for *some* of the changes. For example, the size of additions and deletions relative to the total capitalization of the S&P 500 has been shrinking over time. This could partially explain the disappearance of the index inclusion and deletion returns, because empirically, the size of the added or dropped firm is strongly related to the magnitude of the index effect. We use a simple regression-based approach in the spirit of Fama and French (2001) to show that changes in the composition (as measured by volatility, trading volume, and size relative to total index capitalization) account for only a small portion of changes in the average index addition and deletion returns that we have observed since 2010.

2) Migrations: A second class of explanation is that the *net* demand shock *D* experienced by the typical index addition or deletion is smaller than it appears. We show that in recent years, an increasing percentage of index additions and deletions are "migrations" from the S&P MidCap index. When these stocks are added to the S&P 500 index, they simultaneously leave the S&P MidCap. In these cases, forced buying by S&P 500-tracking funds is simultaneously matched with forced selling from S&P MidCap-tracking funds, leading to a smaller net demand shock. From the 1990s to the present day, migrations went from about 40% of additions to over 80% and this trend toward more migrations is mirrored among S&P 500 index deletions.

The returns to migrations reflect the increasing importance of the S&P MidCap index over time. In the mid-1990s, migration and non-migration additions had average returns of 6.7% and 6.4%, respectively. By the late 2010s, however, direct additions had returns of 2.2%, while migrations had returns of -2.3%. This divergence coincides with the rise of MidCap-focused funds (Sammon and Shim, 2022). More speculatively, it seems possible that one of the reasons for an increased percentage of index migrations is that the S&P 500 index committee has sought to minimize large price impact associated with rebalancing trades.

3) Front running: A third class of explanation is that index additions and deletions have become more predictable over time, attracting arbitrageurs who front-run index demand. In this explanation, sophisticated market participants who anticipate index changes purchase additions and sell deletions before the announcement day, leading the price to move *before* the official announcement. In the extreme case in which index changes could be perfectly anticipated, we would expect no abnormal returns at all during the window of time between announcement and when the index change occurs. We find mixed evidence to support this hypothesis. In recent years, a larger share of the total return leading up to the index change occurs before announcement, although the reason for this is subject to interpretation. In addition, a simple rule of selecting the largest eligible firm has become a better indicator of future S&P 500 addition, further suggestive evidence of predictability. That said, which precise stocks get added are still difficult to predict, and we find very little change in the returns experienced in the 20-trading day period before announcement, where one would expect to see returns if there were substantial anticipation of index changes.

4) Increased liquidity: The last explanation is that the stock market has simply become more efficient in the context of providing liquidity to S&P 500 index additions and deletions. Or, in the context of Equation (1), that M has declined. We show that even after accounting for the increased migrations changing our estimate of the average demand shock D, M has indeed declined by a factor of approximately 20 for index additions, and even more so for index deletions.

Why has the market for index changes become so much more elastic? Part of the answer is that the stock market is more liquid today than in the past, in the sense that trading costs in other settings have also declined since the 1980s and 1990s. However, this is only part of the story, as trading costs have fallen at most by a factor of 10 between the 1990s and the late 2010s. Moreover, the decline in market-wide trading costs predates the disappearance of the index effect.

We identify several market changes that have likely facilitated the greater provision of liquidity around index events. First, over the past 15 years, Wall Street trading desks have increased personnel and computing resources devoted to index trading, with several large players (UBS, Goldman Sachs) having specialized sell-side teams. Large passive investors also employ large teams to study and improve liquidity around rebalancing. Second, the distribution of trading volume has become more concentrated around index change events, facilitating liquidity provision (Chinco and Sammon, 2022). Third, despite the large size of the demand shock experienced by adds and deletes, much of it appears to be accommodated by other institutions. Specifically, although index trackers now buy about 7-8% upon index addition, total institutional ownership barely moves around index changes. We interpret this as professional active investors providing liquidity to passive buyers and sellers.

Overall, the findings suggest an account along the following lines. In the 1980s, index changes were unanticipated, index funds were small, and there was mispricing in the market. As index funds grew larger, the mispricing deepened and turned into an opportunity. As a result, the market adjusted to take advantage of this opportunity, in part by better anticipating inclusions, and in part by creating arrangements where other institutions stood ready to sell to indexers upon inclusions, and companies sold their own stock into these events. This worked to eliminate the anomaly on average, despite demand shocks that continued to grow in magnitude over the 2000s and 2010s. In this sense, the decline of the index effect is much like the evidence for other anomalies, that they decline once they are well recognized by the market (McLean and Pontiff 2016).

There is a long and vibrant literature on downward sloping curves and price pressure for individual stocks. Beginning with Shleifer (1986); Harris and Gurel (1986), and Lynch and Mendenhall (1997), dozens of studies analyze the implications of index changes for stock returns.[2] Cai (2007) and Shahrbabaki (2022) distinguish between fundamental news and price pressure. A more recent literature has studied the effects of rising passive ownership, including Qin and Singal (2015), Bond and Garcia (2018), Garleanu and Pedersen (2018), Kacperczyk et. al. (2018), Buss and Sundaresan (2020), Ernst (2020), Malikov (2020), Lee (2020), Coles et. al. (2022). Koijen and Yogo (2019) and Gabaix and Koijen (2022) study implications for inelastic demand curves for stock prices and the aggregate market. Most closely related to our paper is Bennett, Stulz, and Wang (2022), who first noted the decline in the index inclusion effect, although their focus is on the real effects of index changes, and they study only additions to the S&P 500 between 1997-2017.

The paper proceeds as follows. In Section I, we lay out the puzzle, documenting both the increase in mechanical demand driven by index changes, as well as the puzzling disappearance, on average, of an effect on returns. Section II considers, in turn, each of the potential explanations. Section III concludes.

1. Index tracking and the index inclusion effect 1980-2020

In this section we present the main facts. We first describe how we assemble a list of additions and deletions, before turning to how we identify funds that track the S&P 500. We then present statistics on announcement, effective date, and total returns associated with index changes. Last, we examine whether there is any correlation between net purchases by mutual funds and ETFs tracking the S&P 500 and the returns we observe.

1.1 Data

We obtain data on S&P 500 additions and deletions between 1980 and 2020 from Siblis research. For each index change, Siblis provides the date the change was announced (announcement date) as well as the date the change was implemented (effective date). If the index changes occur on a weekend or trading

[2] Wurgler and Zhuravskaya (2002); Other indices. Kaul, Mehrotra, Morck (2000); Madhavan (2003); Greenwood (2005); Chang, Liskovich, Hong (2015), Patesh and Welch (2017), Madhavan et. al. (2022).

holiday, we mark the next trading day in CRSP as the announcement or effective date. We merge these events to CRSP on date and ticker, and hand match cases on names when either (1) there are multiple CRSP permnos associated with that ticker or (2) there are no CRSP permnos associated with that ticker. Using this method, we can match 752 of the 755 additions and 749 of the 750 deletions between Siblis and CRSP. Before 1990, Siblis does not provide information on announcement dates, so for the pre-1990 additions and deletions, we use data from Barberis, Shleifer and Wurgler (2005).

For purposes of measuring returns, the full sample we just described is sufficient. But, to have a consistent sample to perform all of our analysis, we remove observations which cannot be matched to the Thompson S12 mutual fund holding data on CUSIP either the quarter before or the quarter after the index change. We also exclude cases where the firm was either listed, acquired, delisted for reasons other than an acquisition or was an acquirer (i.e., had an ACPERM in CRSP) within 100 days of the index change.[3] These filters exclude e.g., spin-offs, where a security can be added to the index and then quickly removed.

Columns 2 and 5 of Appendix Table A1 contain the number of observations we can match between Siblis and CRSP each year, while columns 3 and 6 contain the final sample size after we apply all our filters. The number of additions and deletions can differ slightly each year when S&P retains an extra security (because of these retentions, the S&P 500 currently has 505 securities) or due to the small number of observations we cannot match between CRSP and Siblis. Appendix Table A2 verifies that our conclusions about absolute addition and deletion returns declining are not sensitive to sample selection criteria.

1.2 Identifying S&P 500 index trackers

To quantify the amount of money tracking the S&P 500 index, we leverage the Thompson S12 data on the quarterly holdings of mutual funds and ETFs. Our goal is to identify funds that tend to buy additions, or sell deletions, around the time of S&P 500 index change. To this end, for each fund, we count the number of

[3] We exclude cases where the firm is an acquirer because if in the case of a stock merger, there could be significant effects on the number of shares outstanding, which could contaminate our estimates of mechanical buying by S&P 500 index-tracking funds.

times an added stock is not held by the fund the quarter before the addition, and the stock is held by the fund the quarter after addition. Similarly, we count the number of times a dropped stock is held by the fund the quarter before the addition, and the stock is not held by the fund the quarter after the addition. We then divide the sum of these counts by the total number of additions and deletions each year to compute the fraction of index-tracking trades made by each fund.

We classify funds as S&P 500 trackers if, on average across all years that they are present, they perform at least 50% of index-tracking trades each year. [4] According to this methodology, the largest S&P 500 trackers in 2020 were the Vanguard 500 Investor Shares (VFINX) and Admiral Shares (VFIAX), the SPDR S&P 500 ETF Trust (SPY), the Fidelity 500 Index Fund (FXAIX) and the iShares Core S&P 500 ETF (IVV).[5] To allay concerns of overreaching with our classification of S&P 500 funds, in Appendix Figure A1, we show that we obtain a slightly larger estimate for the size of the S&P 500 tracking industry identifying funds based on their objective codes and names instead of changes in holdings.

Having identified the S&P 500 tracking funds, we measure net buying and selling by these funds around index changes. To this end, we add up the shares held by all trackers the quarter before and after the index change. Then, we define net trading by trackers as:

$$Net\ Trading_{i,t} = 100\ \times (Shares\ held_{i,t+1} - Shares\ held_{i,t-1})/Shares\ outstanding_{i,t+1} \qquad (2)$$

where both shares held, and shares outstanding are split-adjusted using the CRSP cumulative factor to adjust shares outstanding.

[4] While at first pass this threshold seems low, it is reasonable given the quarterly nature of the S12 data, as well as the occasional stale data on fund holdings, which means that a true change in holdings in response to an index change may not show up in S12 data for several quarters, which our classification of tracking trades would miss. As a specific example, SPY, the largest S&P 500 ETF, only has annual data before 2008, then switches to quarterly thereafter.

[5] To identify funds based on objective codes we use CRSP objective codes SP and SPSP. To identify funds based on names we follow Appel et. al. (2016) and use variants of "S&P 500", "S and P 500" and "SP 500". We prefer our method of identifying S&P 500 trackers based on changes in holdings to this alternative method because before 1999, the CRSP objective codes (and more broadly, the flag for index funds) are sparsely populated.

Figure 1 shows the average net trading by trackers across adds and drops each year. Consistent with the aggregate rise of passive ownership, in the early 1990s, net buying by trackers of adds was close to 0% of shares outstanding, while now it is over 6%. This pattern is mirrored for drops, going from nearly nothing to selling constituting almost 8% of shares outstanding.

We believe our estimate of net trading by trackers is a lower bound for several reasons. First, our estimates are based only on S12 data i.e., mutual funds and ETFs. There are surely institutions of other types, such as pension funds and endowments, with assets that directly replicate the index, and which are not included in our calculations. In fact, as argued by Chinco and Sammon (2022), the direct replication industry (i.e., investors who internally replicate indices rather than buy index funds) may be larger than the AUM of explicitly passive funds. Another reason our estimates may be too small is that there are shadow indexers who closely track the S&P 500, but not often enough to be classified as index trackers by our method (Mauboussin, Callahan and Majd, 2017). Sell-side research estimates the size of S&P 500 index tracking industry in 2022 to be approximately 13%, about fifty percent higher than our number.[6]

1.3. Inclusion and deletion returns

Figure 2 presents statistics on average returns for S&P 500 index additions and deletions by year. Table 1 presents statistics by year and Table 2 presents statistics based on 10-year periods. We define the abnormal return as:

$$AR_{it} = R_{it} - R_{S\&P\ 500,t} \tag{3}$$

For announcement returns, R is measured as the cumulative return between the trading day before the announcement and the trading day after the announcement. Effective date abnormal returns are also defined according to (3) as the cumulative abnormal return between the day before the implementation of the index change and the trading day after the change. For additions, the average period between the announcement

[6] Author calculations by dividing predicted net purchases by market capitalization for index additions in 2022 UBS report.

and the effective date is 4.8 days; for deletions it is 5.8 days. Our main interest is the total return, defined as the cumulative market-adjusted return from the last trading day before the announcement to the first trading day after the implementation. In principle, the total return captures the price impact resulting from the market absorbing net demand from index traders. For most of our sample, index changes are pre-announced with much of the return (to the extent that there is a return) occurring on announcement. In the early part of our sample, however, index changes are not pre-announced.

Panel A of Figure 2 plots the average index inclusion and deletion effect by year. For additions, the index inclusion effect was 3.42% in the early 1980s, increasing to 7.6% by the 1990s. This is where the effect peaked, as it declined to 5.21% by the 2000s before declining to a statistically insignificant 0.8% in the 2010s. The deletion effect has followed a similar trend toward zero, albeit in a less smooth way. In the 1980s, firms removed from the S&P 500 had cumulative returns of -4.6%, while in the 90s, they had returns of -16.6%. The deletion effect fell in magnitude to -12.3% in the 2000s and disappeared in the 2010s, with an average of -0.6%.

One data point that stands out in Figure 2 is the increase in the inclusion effect in 2020, which drove the uptick in the overall inclusion effect in the late 2010s and 2020. This is due to Tesla being added to the index in November 2020, which, as a fraction of the S&P 500's total market capitalization, was the largest addition of all time.[7] Excluding Tesla, the average inclusion effect in 2020 was -3 basis points. In Section 2.1, we examine whether characteristics e.g., a firm's size relative to the total index capitalization can explain cross-sectional and time series variation in the index inclusion effect.

In Table 2, we break the total index inclusion and deletion effect into the announcement return and the implementation return.[8] The 2nd row of Panel A shows that for additions, the announcement return has been declining over time. In the 1980s, it was 3.4%, falling to 4.1% by the 2000s and to 1% by the late 2010s.

[7] See Arnott, Kalesnik, Wu (2021) for further discussion.

[8] Note that in this table, the announcement return, and implementation return do not have to add up to the total return, as there are typically over 6 days between the announcement and implementation i.e., not all these days are included in the t-1 to t+1 window around each event.

The 3rd row shows that this pattern is mirrored for effective day returns. Specifically, in the 1980s, the implementation return was around 2%, declining to 1% by the 2000s and close to zero by the late 2010s. The last column reports the difference in average returns between the 2000-2009 and 2010-2020 periods. Across the total, announcement and implementation returns, this difference is highly statistically significant.

Panel B of Table 2 replicates Panel A, but for firms dropped from the S&P 500. Like the results for additions, the implementation and announcement returns became indistinguishable from zero by the 2010s. Also like the additions, this difference is strongly statistically significant.

At this point, the puzzle is clear: returns to index changes grew in the 1990s consistent with the growing importance of index funds, but then declined slightly in the 2000s and disappeared, on average, in the 2010s, despite a growing index fund industry. Another potentially more direct way to illustrate the puzzle is to compare, event-by-event, the return to the size of assets tracking the index. We show this in Figure 3, which plots the index inclusion return against net purchases by index trackers. There is no apparent relationship between net purchases and the index inclusion effect, for either additions or deletions. Specifically, for additions, a regression of inclusion returns on net purchases has a negative slope and an R-squared of 2%, while for deletions the same regression has a negative slope and an R-squared of 6%.

2. Explanations

In this section we explore four explanations for the declining index effect in the face of increased index tracking.

2.1 Explanation 1: changing composition of additions and deletions

We have shown that the average returns of S&P 500 additions have been declining over time. A concern with these results is that this trend was driven by a change in the composition of the added and deleted firms, rather than a decline in the nature of the index inclusion effect. For example, larger firms typically experience larger inclusion returns, a phenomenon perhaps driven by benchmarked investors being more likely to buy additions that are a large share of the index, as doing so helps them avoid tracking error (this should not apply to index trackers or ETFs, which should aim to track the index perfectly). As a specific application of this, Tesla was the largest ever firm added to the S&P 500 index, relative to the S&P 500's total market capitalization (over 2%). And, as mentioned above, in 2020 Tesla drove a positive overall average addition effect, experiencing a cumulative market-adjusted announcement return of 5.2% and implementation return of 4.5%.

Another potential shift might be changes in the volatility of additions and deletions. Theoretically, for a demand shock of a given size, price impact should be correlated with fundamental volatility (Kyle 1985, Chacko, Jurek, Stafford 2008). Shifts in this composition – such as for example the addition of high-risk internet stocks in the late 1990s – might explain some of our results.

To quantify the effect of firm characteristics on the inclusion and deletion effects, we run the following regression separately for additions and deletions:

$$Total\ Return_{it} = b_1 turnover_{i,t-1} + b_2\ size_{i,t-1} + b_3 volatility_{i,t-1} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it} \qquad (4)$$

where $Total\ Return_{it}$ is the cumulative return from the day before the announcement to the day after the implementation. $turnover_{i,t-1}$ is the average turnover (defined as volume divided by shares outstanding) in stock *i* over the month before the index changes. To account for the time-series trend toward increased trading volume, we subtract the value-weighted average turnover across all ordinary common shares (share codes 10 and 11) traded on major exchanges (exchange codes 1, 2 and 3) in CRSP over the same period. $size_{i,t-1}$ is the firm's market capitalization on the last day before the announcement of the index change relative to the total market capitalization of the S&P 500 on the same day. We include this, rather than the level of market capitalization on its own, to account for time-variation in firm size and total index capitalization. $volatility_{i,t-1}$ is the sum of daily squared percentage market-adjusted stock returns the month before index addition or deletion.[9] Finally, $1_{era=k}$ are dummy variables for 10-year periods e.g., 1980-

[9] Results are nearly identical using a rolling standard deviation to measure volatility instead of the sum of squared returns.

1989. Note that because we include separate dummies for each era, there is no constant term in the regression.

We start by running the regression in Equation 4 without the controls for past turnover, size, and volatility. This recovers average returns for each of the decades. Note that the averages differ slightly from Table 2 because we lose a handful of observations that don't have information on lagged market capitalization, lagged turnover or lagged volatility. In the last 3 rows, we compare the coefficients between the various decades.

Column 2 of Table 3 shows the full regression results including the controls. The first quantities of interest are the γ_k i.e., the residual average index inclusion effect not explained by the past intensity of trading volume or relative firm size. For the 1980s, 1990s, and 2000s, these coefficients are positive, and statistically significant for the 1990s and 2000s, suggesting that the index inclusion effect in the 1990s and 2000s was not entirely explained by these firm-level characteristics. Further, consistent with our previous results, these coefficients shrink from the 1990s to the 2000s. Finally, these coefficients become negative and significant in the 2010s. Comparing the difference between e.g., the 80s and 2010s, we can see that the decline in the index effect is slightly larger once we condition on the changing characteristics (-2.89% vs. -2.66%). This suggests that changing characteristics cannot explain our results.

Next, we turn to the role of the firm characteristics themselves. The logic of including turnover in the regression is that more liquid firms (i.e., firms with more past trading volume) would potentially have relatively smaller index inclusion effects, because the demand shock upon inclusion is a smaller fraction of average weekly volume. The first row shows that, perhaps surprisingly, the effect of past turnover for additions is positive and weakly statistically significant. In terms of magnitudes, a 1% increase in past turnover would imply a roughly 1% bigger index inclusion effect.

The second row shows that the size of the firm being added to the index matters, and the magnitude is economically large. Specifically, being 1% larger relative to total index capitalization would imply an 18% larger inclusion effect. Admittedly, this is rare, because the average addition is 9 basis points of total index capitalization while the average deletion is 3bp of total index capitalization. Further, additions shrank in relative size between 1980 to 2019, going from an average of 12 basis points to 7 basis points of total index capitalization. But our regression estimates imply this would only explain roughly 50 basis points of the decline in the index inclusion effect. The third control is prior stock-level volatility. Consistent with theory and Wurgler and Zhuravskaya (2002), volatility attracts a positive and significant coefficient.

Column 4 of Table 3 replicates column 2 for S&P 500 index deletions. As with additions, the coefficients are negative for the first three decades, and statistically significant in the 1990s and 2000s. In the 2010s, the sign switches, although the coefficient is not statistically significant. As with additions, the difference between the 1980s and 2010s is even larger once we control for characteristics (5.56% vs. 4.03%). Again, this suggests that changing characteristics of deletions cannot explain the decline in the index removal effect. Turning to the characteristics, past turnover has the expected sign but is statistically insignificant. Like the regression for additions, the size of the deletion matters, and the effect is almost twice as large as the coefficient in column 3.

The bottom line from Table 3 is that the decline in index effects is not explained by a simple shift in the composition or characteristics of the firms being added or deleted from the index. While not the focus of our paper, composition effects are important for a handful of years, such as for example the anomalous large average return in 2020 driven by the Tesla inclusion.

2.2 Explanation 2: Index Migrations

A second explanation is that we have mismeasured the net demand D (in Eq. 1), and that properly measured demand for additions has fallen, with similar results for deletions. A notable type of index change for which this holds is so-called index "migrations". An index change is a migration when it moves from the S&P MidCap index to the S&P 500 or vice versa. An example of this would be Targa Resources (Ticker: TRGP) which was dropped from the MidCap and added to the S&P 500 on October 6, 2022. This differs from direct additions, where a firm is added to the S&P 500 from outside the MidCap and SmallCap universe. An example of this is PG&E (Ticker: PCG) which was added to the S&P 500 on October 3, 2022.

When a stock migrates from the S&P MidCap to the S&P 500, MidCap-tracking funds sell, and 500-tracking funds buy. Further, over the last 30 years, the passive ownership of mid-cap stocks (i.e., the fraction of these stocks' shares outstanding) has grown dramatically (Sammon and Shim, 2022).[10] As mid-cap focused funds have grown, so has the magnitude of the negative demand shock, which we would expect to reduce the price impact of a firm being added to the S&P 500. Jointly, these facts imply that migrations should have smaller index inclusion effects than direct additions, and the difference between migrations and non-migrations should be increasing over time.

To quantify differences between migrations and direct additions, we start by obtaining data on S&P MidCap index changes from Siblis research. Unlike our dataset on S&P 500 index changes, which starts in 1980, the MidCap changes dataset starts in 1995. We follow a similar procedure to the one described in Section 1.1 to match these observations to CRSP. Figure 4 shows that migrations have become an increasingly large share of additions and deletions. In the mid-1990s, migrations were about 40% of additions and 0% of drops. In recent years, they both make up over 60% of index changes.[11]

To fully understand the impact of migrations, we need to estimate capital linked to S&P MidCap index. This is more challenging than the S&P 500 because the largest S&P MidCap funds infrequently report their holdings for much of the sample period. Instead, each year, we identify S&P MidCap 400 index funds based on names and correlations. To identify funds based on names we require that the fund name contain either variants of "S&P", "SPDR" or "S and P" as well as variants of "400" or "MidCap". To identify funds based on correlations, we first restrict to the universe of mid-cap focused equity funds (those with either CRSP objective code "EDCM" or a Lipper objective code that starts with MC) that do not include variants of "Vanguard" or "Russell" in the name. Among these funds, we classify them as S&P MidCap 400 trackers if their returns have a correlation of at least 99.5% with the index itself for three years in a row. According to

[10] The passive ownership industry being overweight mid-cap stocks is not specific to the S&P MidCap universe in particular, but stocks in that part of the firm-size distribution.

[11] The pattern is even more dramatic if we consider all additions rather than our subsample, as migrations made up only 20% of all additions in the mid-1990s (vs. 40% in our sample).

this methodology, the largest S&P MidCap trackers in 2020 were the iShares Core S&P Mid-Cap ETF (IJH), the SPDR S&P MidCap 400 ETF (MDY), the iShares S&P Mid-Cap 400 Growth and Value ETFs (IJK and IJJ), as well as the SPDR Portfolio S&P 400 Mid Cap ETF (SPMD).

Figure 5 shows the sum of these funds' AUM, scaled by the total market capitalization of the S&P MidCap 400 index. As can be seen, dollars tracking the MidCap have grown substantially over time, reaching nearly 8% of capitalization, slightly more than that of the S&P 500 that we showed earlier. All of this suggests that in recent years, stocks that are added to the S&P 500 from the MidCap experience a slight net selling pressure.

We now turn to returns. We compare the average returns by year of migrations from the S&P MidCap to direct additions.[12] The bottom left panel of Figure 6 shows that direct adds to the S&P 500 have experienced a decline in the index inclusion effect over the past 25 years. Specifically, for direct additions, the index inclusion effect was 9.6% in the late 90s, 7.5% in the early 2000s, 5.1% in the late 2000s, 1.6% in the early 2010s and 4.1% in the late 2010s and 2020. The large positive return in the last period is driven by Tesla, which as discussed above had a massive return between the announcement and effective date.[13]

The bottom right panel shows that, consistent with the increased size of the offsetting demand shock due to the rise of MidCap funds, there has been a significant decline in the index inclusion effect for migrations. For migrations, the index inclusion effect was 5.8% in the late 1990s, 5.9% in the early 2000s and 1.6% in the late 2000s. By the 2010s, this effect became negative, at -2.6% for both the early and late 2010s.

Interestingly, these mechanisms don't seem to apply equally to deletions. When a firm migrates from the S&P 500 to the MidCap, the mechanical selling by S&P 500 funds should be met by mechanical buying by MidCap funds. Based on the results on migration additions, we would expect that the drops to the MidCap

[12] We exclude migrations from the S&P SmallCap to the S&P 500 because in our sample, few firms migrate between the large and small cap indices directly.

[13] Another way that Tesla's addition was unusual is that there was a 32-day gap between the announcement of its addition and the implementation of the index change. So, the total cumulative market adjusted return to Tesla may also be high because other good news about Tesla was released between the announcement date and effective date.

should have had returns which become less negative over time. The top right panel of Figure 6, however, shows mixed evidence on this, as returns to migrations initially increased from 1995-2015, but then decreased thereafter. Further, the top left panel shows that most of the decline (in magnitude) of the index deletion effect came from firms which were dropped to outside the index, where presumably there is no offsetting demand shock. For such firms, the index removal effect was -13.0% in the late 1990s, -16.1% in the early 2000s, -12.4% in the late 2000s, and finally becoming insignificantly different from zero by the late 2010s.

To sum up, migrations are helpful for understanding some of the decline in the returns associated with additions, but not very helpful for explaining deletions. We return to the migrations in section 2.4 where we assess the overall change in liquidity associated with index changes.

2.3 Explanation 3: Predictability of Index Changes

As the amount of money tracking various indices has grown, so has the industry of investors trying to take advantage of the trades they make. For example, an article in Bloomberg describes how a 20-person team at Goldman Sachs earned $700 million a year in profit betting on index additions and deletions across a variety of indexes. This behavior is not restricted to proprietary trading desks. In fact, many investment banks (e.g., UBS) publish short-lists of stocks they think will be added to various indices for their wealth-management clients.

If index additions have become more predictable, we should see certain patterns emerge in pre- and post- addition returns. Suppose, to start, that index changes were completely unpredictable. In this case prices should rise around announcement, followed by reversion over very long horizons. Alternatively, if additions become more predictable, we should see an increase in price before announcement, coupled with reversion in the long run. It is hard to test this scenario, however, because of the endogeneity of index additions. Namely, non-index stocks that go up in value are more likely to be added to the index in the first place.

We start by looking at cumulative pre-addition returns. To this end, we calculate the cumulative market-adjusted returns starting 100 trading days before the announcement of the index change to 10 trading days after the announcement. Figure 7 shows that over the past 30 years, the total price change over this period has been roughly equal (in the 1980s, the total price change was less). The difference, however, is that the price spike on the announcement of the index change has become less sharp over time. Specifically, the cumulative market-adjusted return up to the day before the announcement was 6.4% in the 1990s, 9.1% in the 2000s and 11.6% in the 2010s. Then, the cumulative return up to the day after the announcement was 12.1% in the 1990s, 13.8% in the 2000s and 14.7% in the 2010s. Finally, by 11 trading days after the announcement, in every decade the cumulative returns are between 13 and 14%. So, even though the total distance traveled is similar, in more recent years, more of this occurred before the announcement while in past years most of it happened before.

As we noted, one issue with Figure 7 is that all of this is defined ex-post i.e., we are looking at the firms that *ended up* getting added. It could be, however, that S&P has become more likely to add firms which went up a lot in the pre-announcement period over time. In short, while the evidence is consistent with higher predictability, it is not dispositive, because one could equally interpret this evidence as saying that S&P 500 has become better at adding the best performing stocks, as we show below.

Table 4 summarizes the pre-announcement returns shown in Figure 7. For each era, and separately for additions and deletions, we show average abnormal returns for the window beginning *k* days before announcement and ending one day before the announcement, for k= 10, 20, 50, and 100. For purposes of discussion, we focus on the shorter windows because they are less confounded by selection, and because front-running activity seems more likely in the immediate window before the event. As can be seen, additions had average [-20,-1] abnormal returns of 2.15% in the 1990s compared to 2.47% in the 2010s. Deletions had average [-20,-1] abnormal returns of -14.7% in the 1990s compared to -2.4% in the 2010s. In the immediate window preceding the event, then, there is no evidence of front running for additions and the evidence goes the other way for deletions. At longer windows, however, the picture is murkier. Additions had average [-100,-1] abnormal returns of 10.29% in the 1990s compared to 19.3% today.

Another way to test whether additions have become more predictable is to see whether, in fact, we can predict which stocks are added to the index. Here we focus on the most salient characteristics of index additions, namely that they are large stocks that are not in the index and develop a simple model of S&P's index inclusion rule. To quantify this, each month, we compute the market capitalization rank of all ordinary common shares traded on major exchanges outside the index. Then, in Figure 8, we plot the average rank of firms that end up getting added, as well as the 25th and 75th percentile of these ranks.[14] Of course, this is an imperfect ranking system as it does not account for (a) the float-adjustment made by S&P (b) the fact that S&P may add non-ordinary common shares and (c) S&P's other rules such as profitability, size, liquidity, and insider ownership.[15] Panel A shows that over time, it seems as though S&P has moved to picking larger firms. The picking of larger firms also seems to have become more consistent, as the interquartile range has declined. This, however, does not mean it's easy to predict additions using size alone, as the average rank of firms added in the last 10 years is around 50. Further, as can be seen, the interquartile range can be quite large, spanning about 40 ranks, suggesting significant randomness in which firms end up getting added (at least on the size dimension).

One concern with the results in Panel A is that the number of publicly listed firms has been declining (Doidge, Karolyi and Stulz, 2017). This trend could mechanically increase the rank of added firms if S&P always chose firms in the same part of the firm-size distribution. To address this concern, in Panel B, we plot the percentile rank of added firms. The time-series trend is similar to the pattern in Panel A, suggesting that the decline in the universe of public firms does not explain this result.

To sum up, the evidence on front-running is mixed. Index changes are more forecastable in the last decade than they were in the past. But we do not observe meaningful changes in returns in the short windows leading up to announcement, but we do observe changes at longer horizons.

[14] In a small subset of years, the mean is above the 75th percentile – these are years where one or two extremely low ranked firms were added to the index.

[15] There are huge firms, such as publicly-listed private equity firms, that do not meet S&P criteria in spite of their size.

2.4 Explanation 4: Higher liquidity

A fourth class of explanation is that the market is more efficient today at accommodating the required changes in ownership associated with index addition and deletion. Or, in the context of Equation 1, that the multiplier *M* on demand shocks has declined.

To estimate how much liquidity has changed, we take means of Equation 1 by decade, and rewrite it to reflect the fact that the average net demand shock D varies for index migrations compared to non-migrations:

$$\overline{Price\ Impact} = M \times \bar{D} = M \times (w \cdot \bar{D}_{Migrations} + (1-w) \cdot \bar{D}_{NonMigrations}) \qquad (5)$$

Our goal is to estimate how much M has declined. This exercise is only possible beginning in 1995, when we have information on index migrations. Table 5 shows these results, separately for index additions and deletions. For example, in the 2010-2020 period, the average abnormal return for 150 additions was 0.80%. 41% of additions were migrations with an average net demand shock of -0.45% of market cap; the remaining 59% of additions experienced a net average demand shock of 4.86%. This yields an estimate of M of 0.30, or equivalently, a demand elasticity of -3.39. Repeating this episode era by era, the multiplier M has fallen by a factor of more than 20, from 6.7 in the late 1990s to 0.30 in the last decade. A similar pattern appears for index deletions, with M falling from 10.84 in the late 1990s to 0.33 in the last decade. In summary, even after accounting for the impact of index migrations, liquidity has increased substantially.[16]

How and why did the market become more efficient at accommodating index changes? Below we explore four forces associated with these changes (1) increases in market liquidity and reductions in trading

[16] To keep our results comparable throughout the paper, Table 5 is based on the total returns from the day before announcement to the day after implementation. However, as we noted earlier, our conclusions may vary if we account for potential front-running, in the sense that total price impact may play out over a longer window. For this reason, we have also estimated Table 5 using a longer horizon return beginning 20 trading days before announcement and ending a day after implementation. Here, the results are similar, but smaller, with M falling by a factor of 8 for additions and 9 for deletions.

costs in other settings (2) coordination of trading around index changes, and (3) accommodation of index changes by active managers (4) accommodation by firms issuing stock. We find evidence for all but the last.

Increases in overall market liquidity

The US stock market has become more liquid overall since the 1980s and 1990s, in the sense that it has gotten cheaper to trade without moving the price. We consider two ways of measuring trading costs. Amihud and Mendelson (1986) suggest the bid ask spread as a simple measure of trading costs. To quantify this, we use the WRDS intraday indicators suite to obtain measures of the bid-ask spread based on high frequency data. This dataset uses the method in Holden and Jacobson (2014) to compute the percent effective spread. In words, the percent effective spread is the percent distance away from the midpoint that the (value-weighted) average trade occurs at each day. Given that our study spans 1980-2020, we need to leverage both the second-based version of TAQ, which runs from 1993-2014, and the millisecond-based version of TAQ, which runs from 2003-present. We do not have a good measure of trading costs before 1993.

Figure 9 plots the value-weighted effective spread for all ordinary common shares traded on major exchanges. The blue line represents this quantity computed using the second-based TAQ data, while the red line represents the same quantity for the millisecond-based TAQ data. Value-weighted average effective spreads have experienced a large time-series decline, from 60bp to 6bp. The decline is similar when examining an equal-weighted average of the bottom 100 stocks by market capitalization in the S&P 500.

The bid-ask spread captures costs associated with small trades near the midpoint. But the type of trades executed on days of index changes likely don't fit this description: the fraction of shares that need to be purchased by index funds are enormous, now making up over 7% of total shares outstanding. For this reason, we also examine implementation shortfall collected from Virtu financial. The implementation shortfall is the difference between the arrival price and the execution price for a trade. Figure 10 shows that, over our sample, implementation shortfall fell significantly less than the average bid-ask spread.

Coordination and specialization of trading

Over the past 15 years, several Wall Street trading desks have increased personnel and computing resources devoted to index trading. Large players, including UBS, Goldman Sachs, and Bank of America have specialized sell-side teams. Passive fund managers also employ large teams to study and improve liquidity around rebalancing. We have confirmed this in conversations with several large index investors, including Blackrock, which employs a team of over 60 people in index research alone.

Trading around index changes has become increasingly concentrated and transparent. We interpret this using the logic of Admati and Pfleiderer (1988): to coordinate on this "sunspot", index providers have moved to a system of disclosing ahead of time which stocks they are going to trade and when (Li, 2022). To quantify this, following Chinco and Sammon (2022), for each addition or deletion, we compute the total trading volume in a +/- 22 trading-day window around the event. Then, we compute the share of volume on each day and take an average across all firms each in a set of 10-year blocks. Figure 11 shows that for additions in the early 1990s, about 15% of trading around the index changes happened on the effective date itself, while now it is closer to 30%. Panel B of Figure 11 shows a similar pattern for deletions. Such coordination may have facilitated improvements in liquidity.

Accommodation by other institutions

Liquidity around index changes has increased, but who provides it? Below we show that liquidity is provided on average by other institutions exiting their positions. In other words, while a large, dedicated group of mutual funds and ETFs *must* buy, on average, *total* institutional ownership changes very little around these events. To quantify this, we obtain data on institutional ownership from Thompson 13F. Specifically, we examine changes in 13F ownership from the quarter before to the quarter after the index change. These changes are tabulated in Table 6, which compares the changes in ownership by S&P 500 trackers to the total change in institutional ownership. Despite the rise in the change in tracker ownership, there has been (if anything) a decline in the change in 13F ownership. For example, the table shows that for the average addition in 2020, index trackers buy 6.85% of shares outstanding. However, institutional ownership falls by 0.66% of shares outstanding. This suggests that other institutions have stepped up to meet the buying and selling pressure from S&P 500 funds. The same pattern appears for deletions: in 2020, index trackers sell an average of 7.5% of shares outstanding upon deletion, but institutional ownership overall falls by only 0.75%.

We also examine the net trading behavior of active and passive mutual funds and ETFs around S&P 500 index additions and deletions. We identify passive funds in the S12 data using the methodology in Appel et. al. (2016) and define active funds as all remaining funds. Column 3 of Table 6 shows that, on average, passive funds buy a smaller percentage of additions' shares outstanding than S&P 500 trackers. This is consistent with some additions being migrations, whereby MidCap-tracking passive funds sell shares to S&P 500-tracking funds, shrinking net passive demand. Column 4 shows that active mutual funds are not the group providing liquidity, as their average net demand is roughly zero. This implies that non-S12 filing institutions (e.g., hedge funds, pension fund, endowments) are the primary liquidity providers around addition events.

Accommodation by corporate share issuance?

A last hypothesis is that index additions are partially accommodated by firms that issue shares into the rebalance. A few high-profile examples of this, such as CoStar upon its addition to the S&P 500 in 2018, where it concurrently issued $750 million of new equity, suggest the possibility of this phenomenon being important. We have investigated changes in split adjusted shares outstanding around all S&P 500 index additions and deletions beginning in 1980. The fraction of firms that have issued stock near S&P 500 membership changes increased somewhat in the 2000s, but then declined in the 2010s. Large stock issuances around index changes are rare. We conclude that this is not a major force driving the improvement in liquidity around index rebalances.

2.5 Discussion

Our findings suggest the following sequence of events. In the 1980s, index changes were unanticipated, but index funds were small, so addition and deletions effects were relatively modest. As index tracking grew larger throughout the 1990s, the mispricing deepened and turned into an opportunity. As a result, the market adjusted to take advantage of this opportunity, in part by better anticipating inclusions, and in part by creating arrangements where other institutions stood ready to sell to indexers upon inclusions.

The index provider, S&P also adapted to mitigate market froth associated with index changes. In particular, the S&P 500 grew to rely more on index migrations, which helped to reduce overall price impact, and benefitted from increasing assets tracking midcap indexes. Together, these forces worked to eliminate the index addition and deletion anomalies on average, despite demand shocks that continued to grow in magnitude over the 2000s and 2010s. In this sense, the decline of the index effect is much like the evidence for other anomalies, that they decline once they are well recognized by the market (McLean and Pontiff 2016).

3. Conclusion

According to efficient markets theory, if a class of investors were to buy or sell a stock for reasons unrelated to fundamentals, well-capitalized arbitrageurs should respond aggressively to provide liquidity, limiting the price impact. The well-known index effect, whereby a stock added to an index such as the S&P 500 goes up in price, is often held up as an example of market inefficiency. The notion of a downward sloping demand curve is a key ingredient in most behavioral finance models of the stock market.

Over the past decade, the well-known index effect for the S&P 500 has disappeared, with the average addition or deletion experiencing abnormal returns near zero. In this paper, we consider four explanations why this happened. To sum up, our assessment is that the declining index effect is driven by primarily two factors: an increase in migrations over time from the S&P MidCap Index, and an overall increase in the market's ability to provide liquidity to index changes. We cannot rule out that a third factor, increased predictability of index changes, played some role. Overall then, we conclude that when demand shocks become regular and repeated, competitive markets adapt over time to minimize price impact, in the spirit of Lo's (2004) adaptive markets hypothesis.

Our findings raise two additional questions. First, S&P 500 index changes have been around since 1957, but it took until the 2010s for the market to evolve to provide meaningful liquidity around index changes and neutralize the price impact. Why did it take so long? Second, given the growth of other indexes such as the Russell and MSCI global indexes, it raises the question of whether inclusion and deletion anomalies in these other indexes will similarly disappear over time. We expect subsequent work to shed light on how the channels we have discussed apply in these different settings and at what speed markets adapt to eliminate anomalies.

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Figure 1. Net buying and selling by S&P 500 index trackers, by year.

Net buying and selling are defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding. Equal weighted average among events by year. Red line represents a LOWESS filter (bandwidth = 0.8).

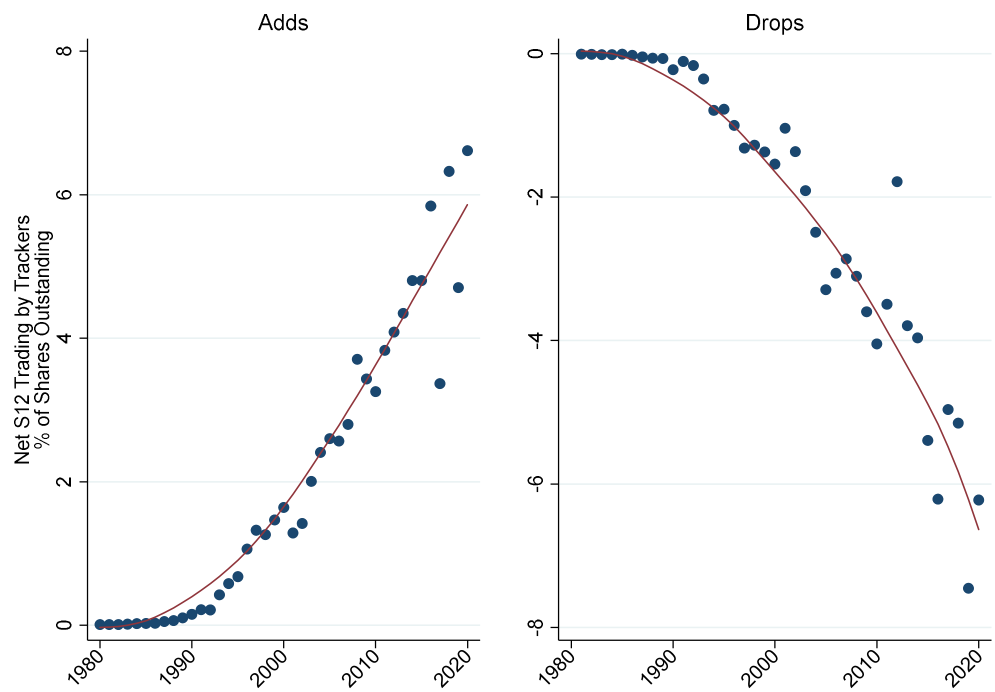
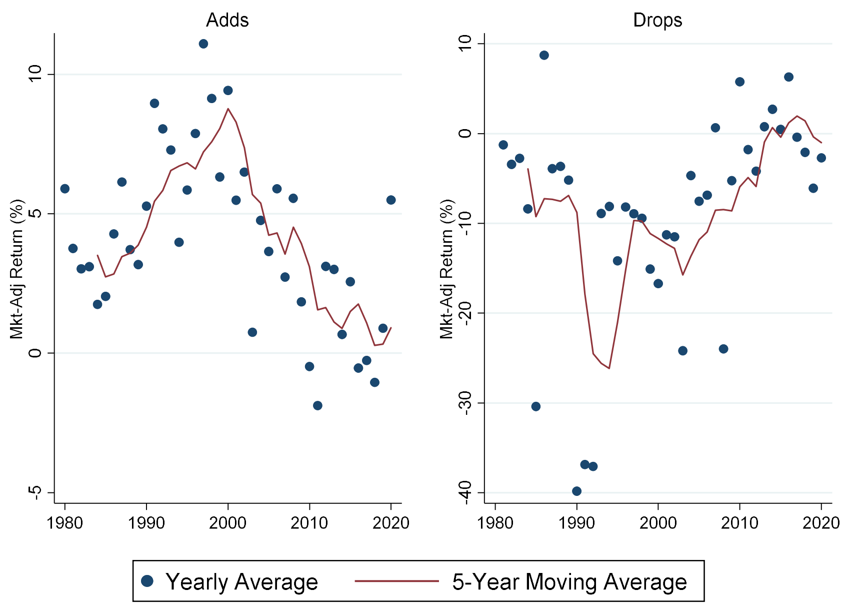


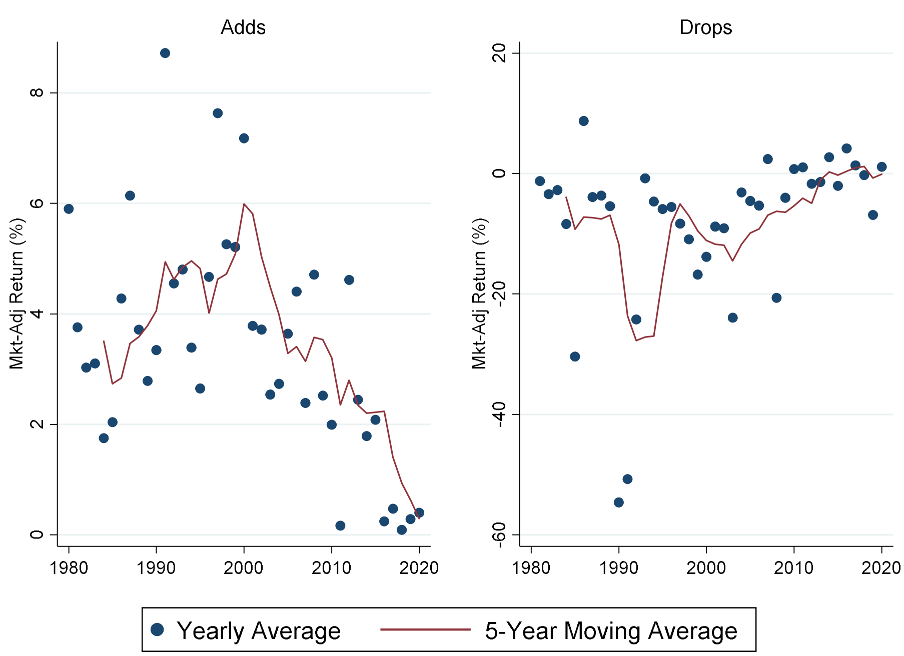
Figure 2. Average index effect by year.

For each event, we compute the cumulative market-adjusted return over the period of interest. Blue dots represent the average for adds and drops each year. The red line represents the 5-year moving average of this quantity, starting 5 years into our sample.

Panel A. Total effect: returns from the day before the announcement to the day after the implementation.



Panel B. Announcement effect: return from the day before to the day after the announcement.



Panel C. Implementation effect: return from the day before to the day after the effective date.

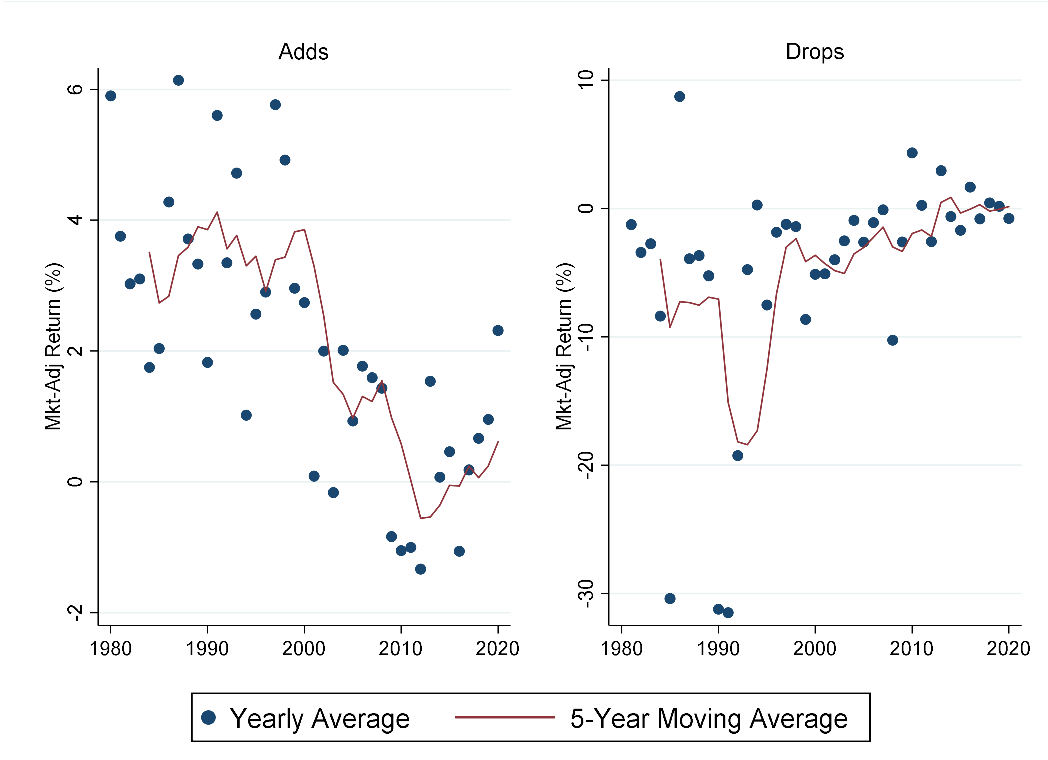


Figure 3. Forced buying and selling, and the index effect.

Each point represents an individual addition or deletion event. Mechanical buying is defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). Y-axis represents the total inclusion effect return i.e., the cumulative return from the day before the announcement to the day after the implementation.

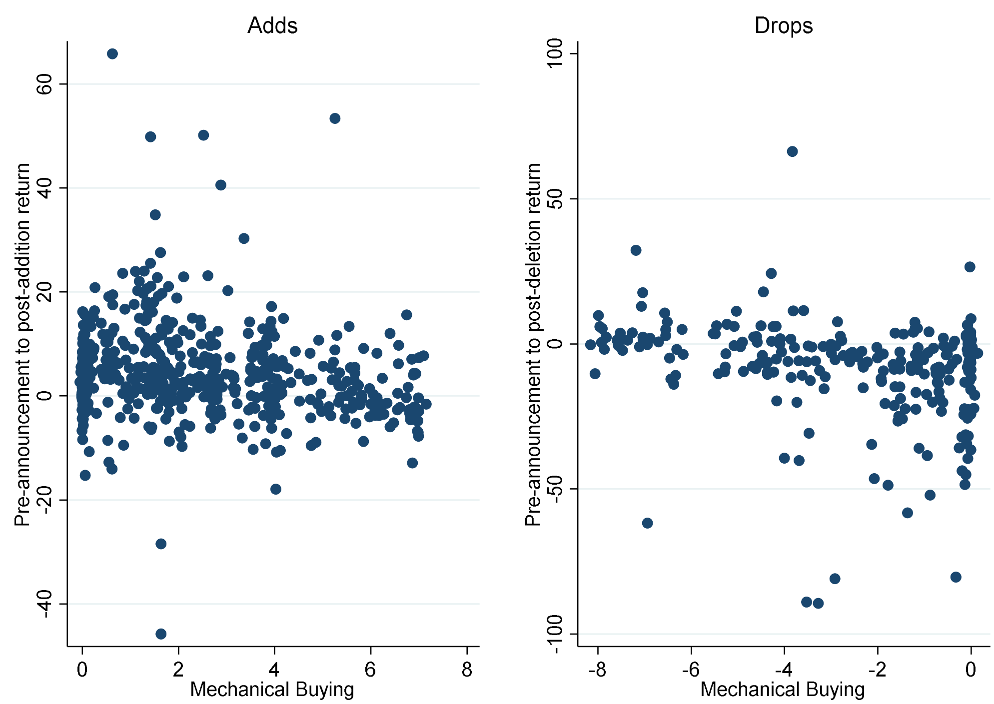


Figure 4. Migrations as a fraction of S&P 500 additions and deletions.

Each year, we identify migration additions as firms which are simultaneously added to the S&P 500 and dropped from the S&P MidCap. We identify migration deletions as firms which are simultaneously dropped from the S&P 500 and added to the S&P MidCap. Then we compute the fraction of additions and deletions in our sample which are migrations each year. Green and blue lines represent LOWESS filters (bandwidth=0.8).

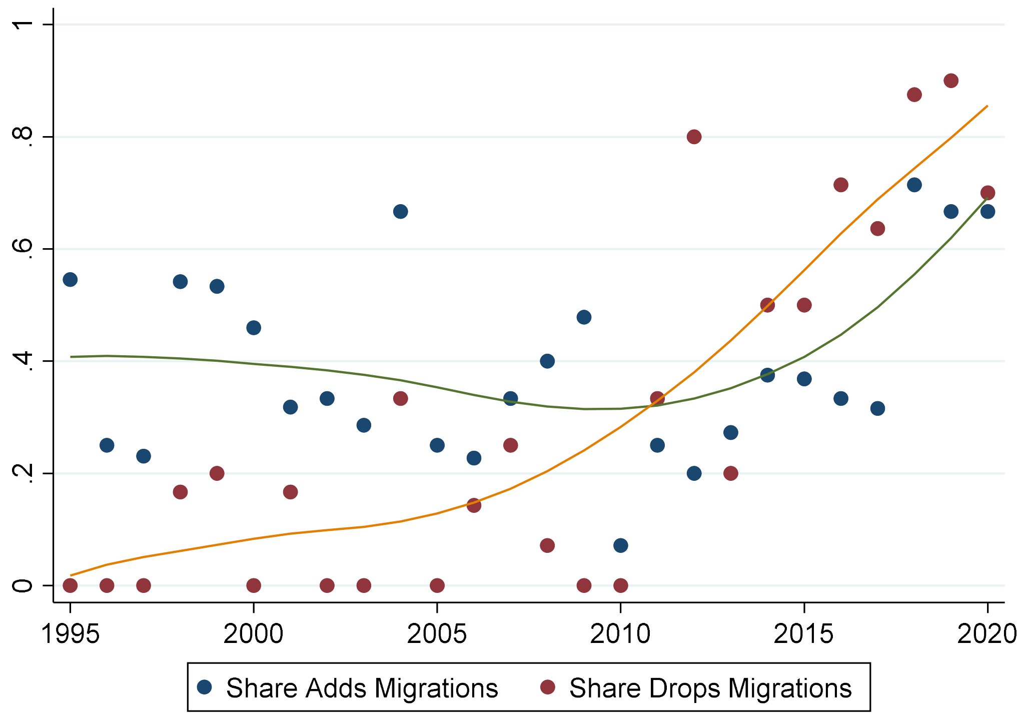


Figure 5. Percent of S&P MidCap 400 Owned by Index Trackers.

Each year, we identify S&P MidCap 400 index funds based on names and correlations. To identify funds based on names we require that the fund name contain either variants of "S&P", "SPDR" or "S and P" as well as variants of "400" or "MidCap". To identify funds based on correlations, we first restrict to the universe of mid-cap focused equity funds (those with either CRSP objective code "EDCM" or a Lipper objective code that starts with MC) that do not include variants of "Vanguard" or "Russell" in the name. Among these funds, we classify them as S&P MidCap 400 trackers if their returns have a correlation of at least 99.5% with the index itself for three years in a row. Finally, we add up the total assets of these funds, and divide them by the total market capitalization of the S&P MidCap 400 index.

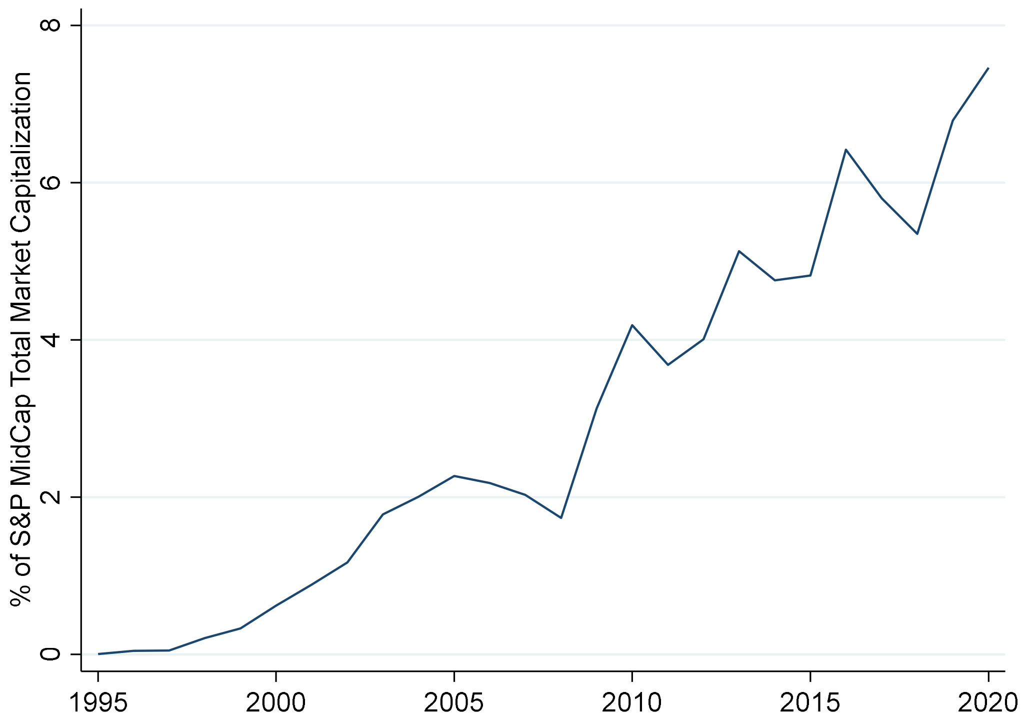


Figure 6. Comparing addition and deletion returns across index migrations and "direct adds" or "direct deletions"

For each event, we compute the market-adjusted return from the day before the announcement to the day after the implementation. Blue dots represent the average of this quantity each year. The red line represents a LOWESS filter (bandwidth=0.8).

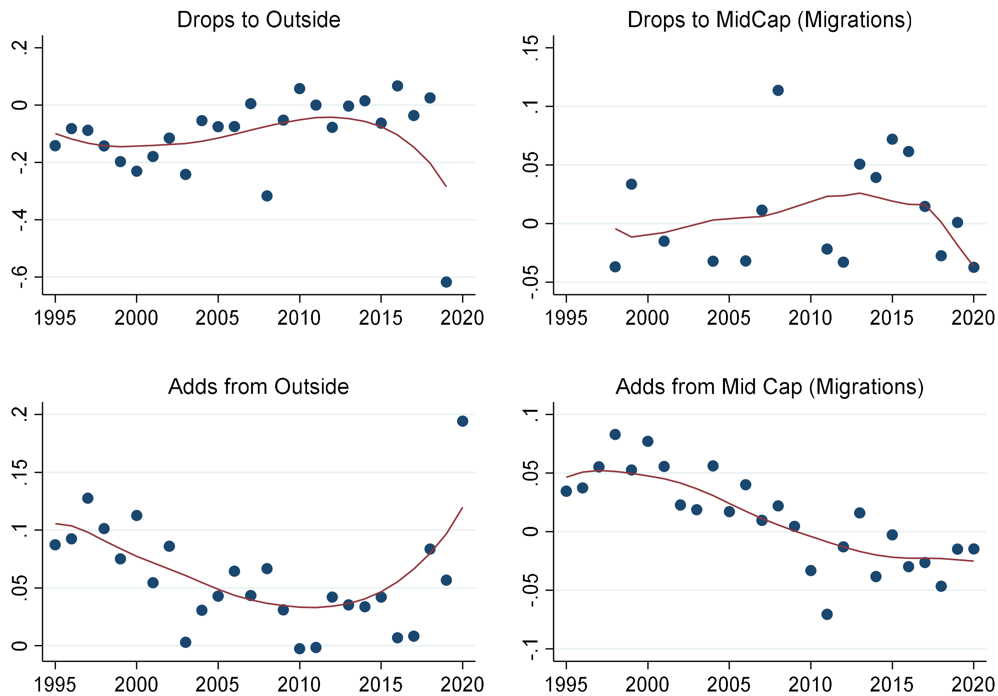
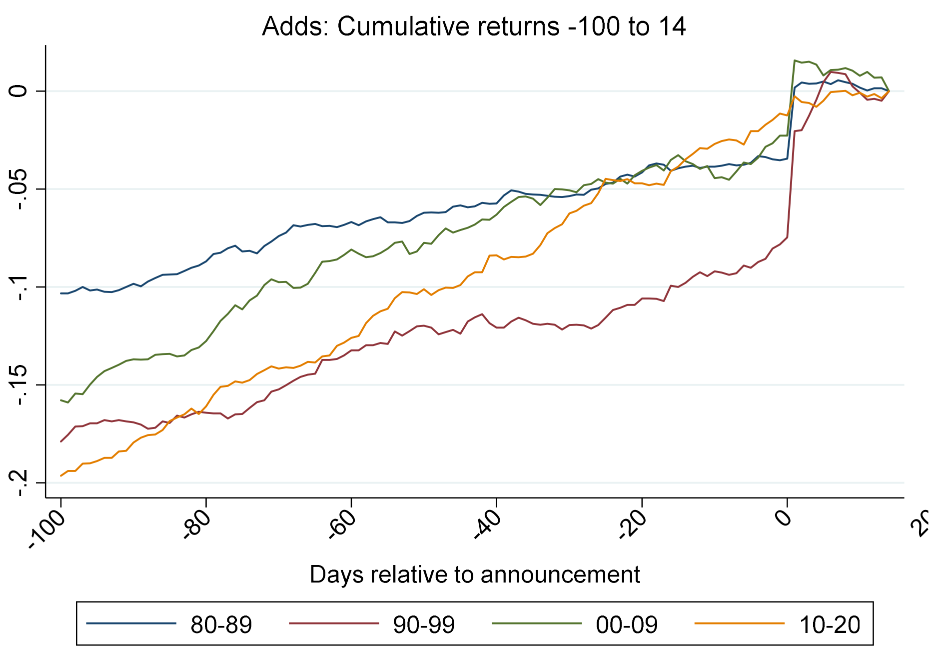


Figure 7. Cumulative pre-addition and pre-deletion market-adjusted returns.

Average cumulative returns in event time, pooled for 1980-1989, 1990-1999, 2000-2009, and 2010-2020. Normalized to 0 ten trading days after the announcement.



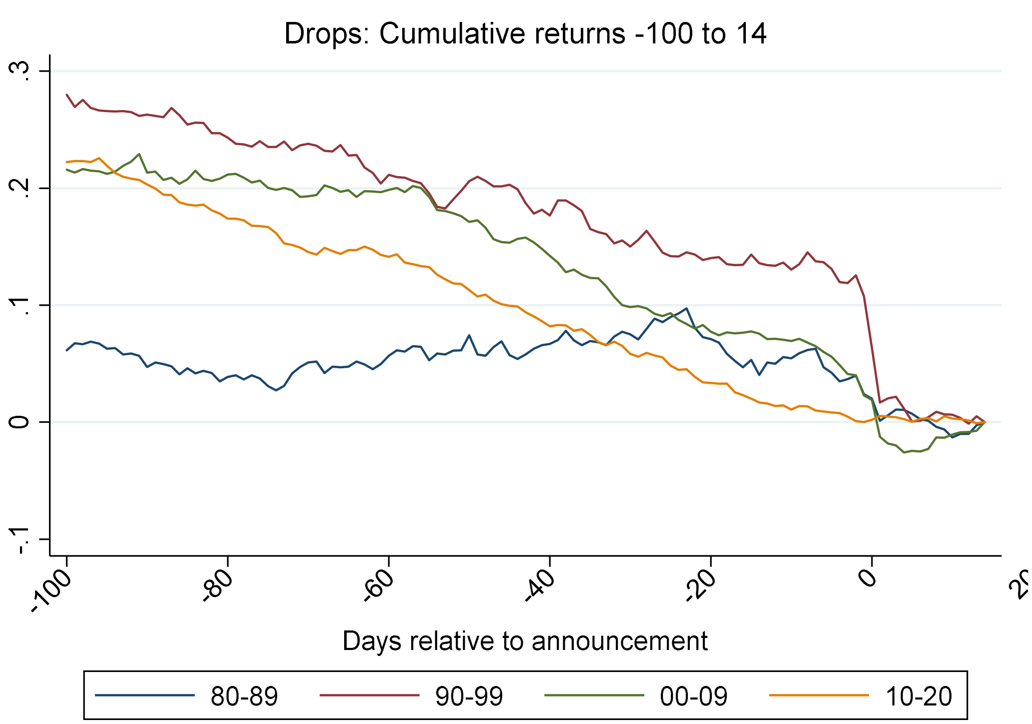
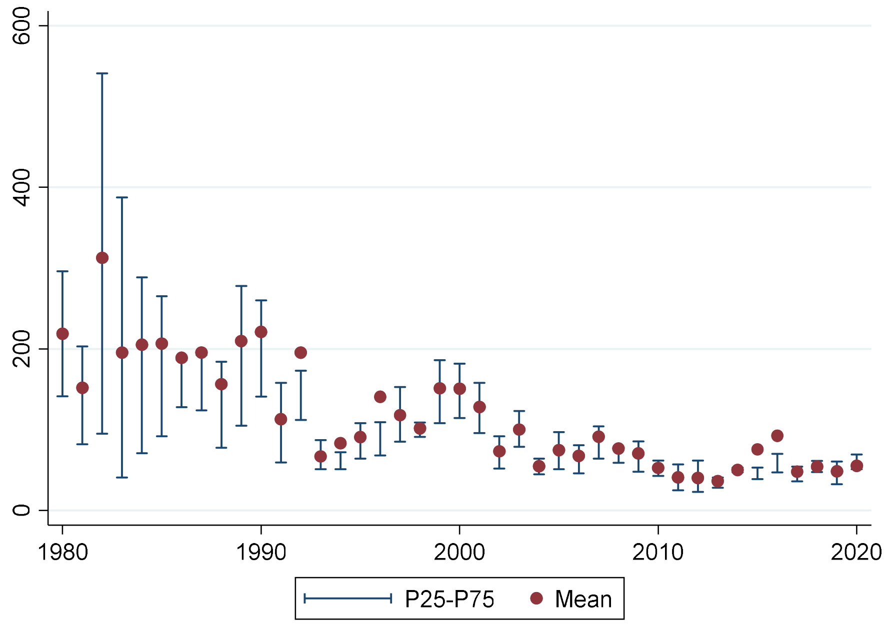


Figure 8. Rank of additions among stocks outside the index by year.

Each month, we rank all ordinary common shares traded on major exchanges outside the S&P 500 by market capitalization. Then, each year, we plot the average rank, as well as the 25th percentile and 75th percentile ranks of stocks which ended up being added the month before their index addition. Panel A shows raw ranks; Panel B shows percentile ranks i.e., rank divided by the total number of ordinary common shares traded on major exchanges not in the S&P 500.

Panel A. Ranks



Panel B. Percentile Ranks

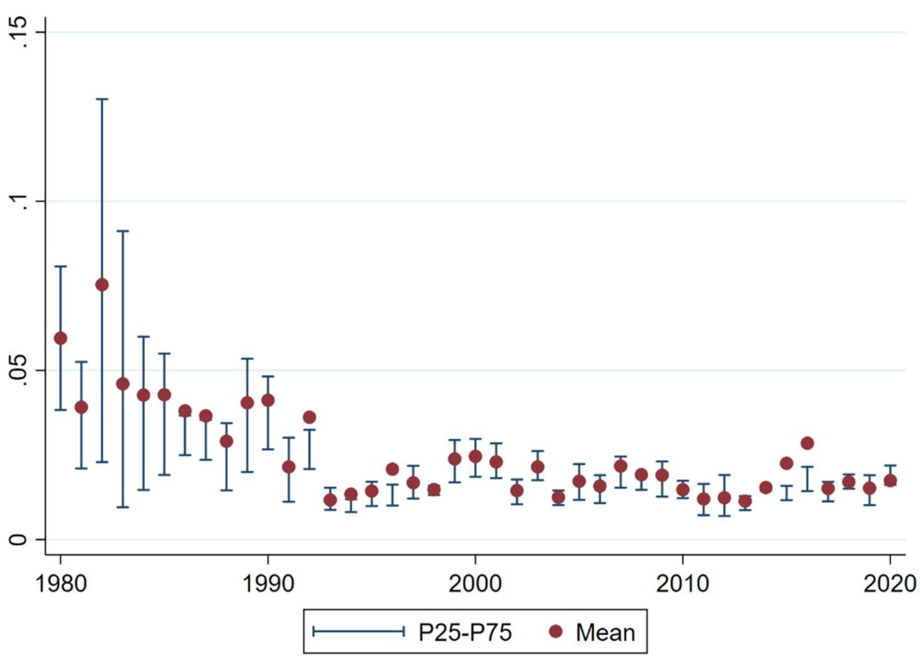


Figure 9. Value-weighted average effective bid-ask spreads.

Percentage effective spread computed from TAQ data using the method in Holden and Jacobson (2014). Weights are proportional to each firm's one-month lagged market capitalization. The blue dots represent estimates from the second-based TAQ data, while the red dots represent estimates from the millisecond-based TAQ data.

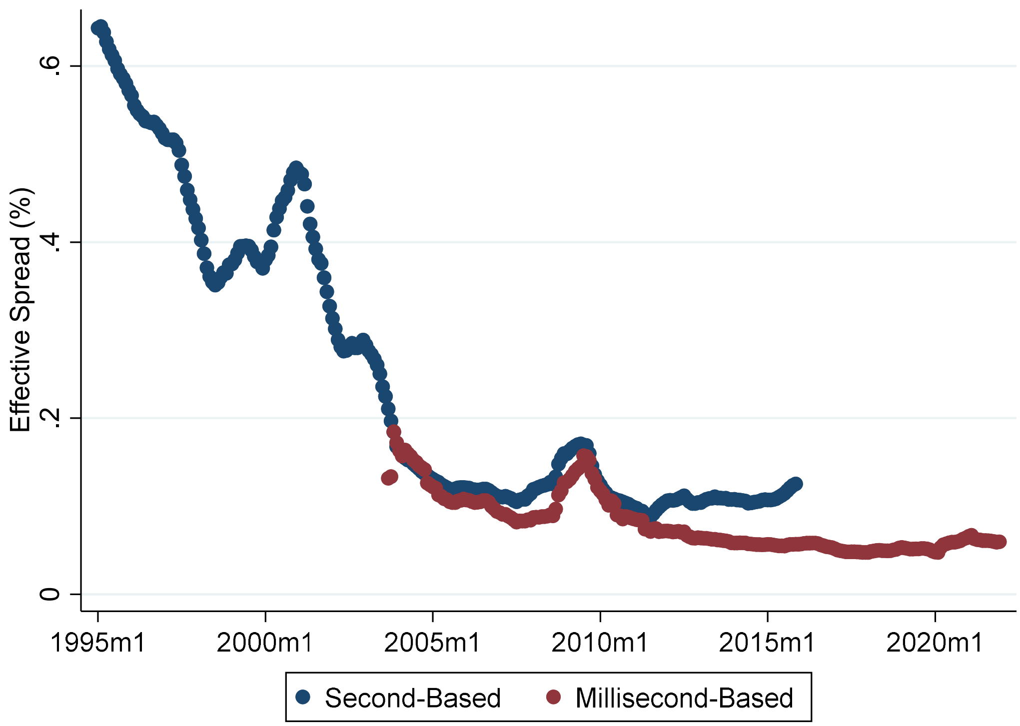


Figure 10. Implementation shortfall, midcap stocks

Implementation shortfall is the difference, or slippage, between the arrival price and the execution price for a trade. The plot shows average implementation shortfall from 2009 through 2021, using data from ITG and Virtu Financial, for midcap stocks.

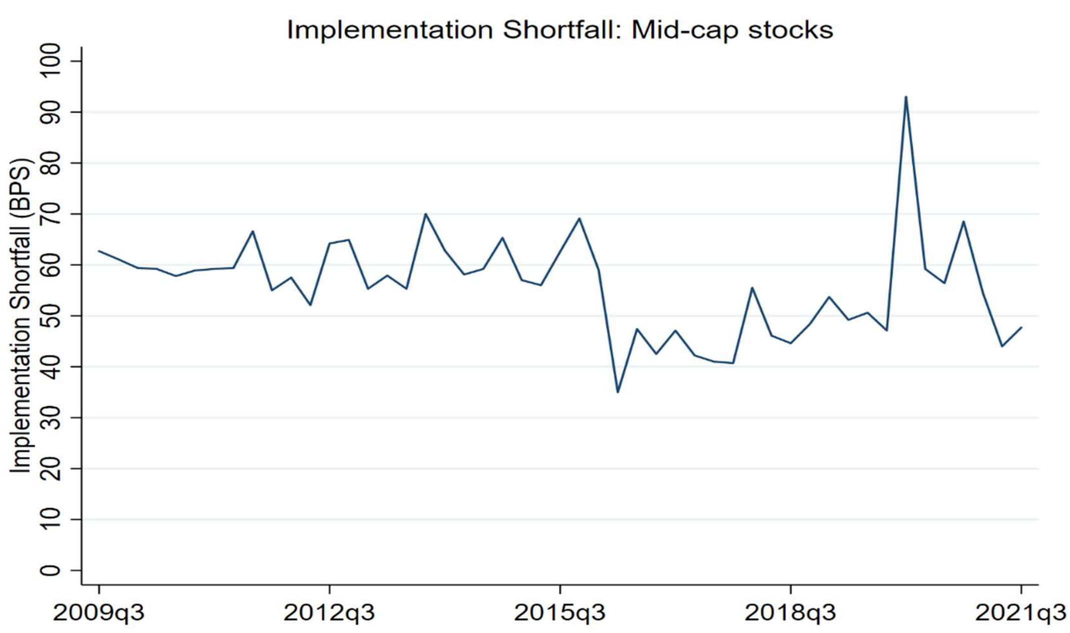
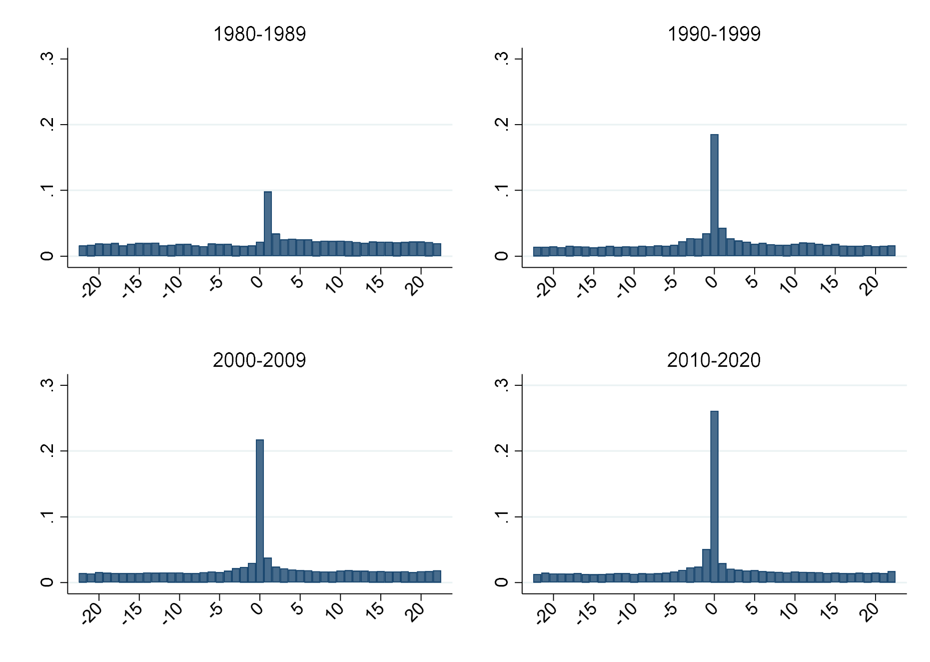


Figure 11. Share of volume on days -22 to +22 around the effective index change.

For each addition or deletion, we compute the total trading volume in a +/- 22 trading-day window around the event. Then, we compute the share of volume on each day and take an average across all firms each in each 10-year block.

Panel A. Additions



Panel B. Deletions

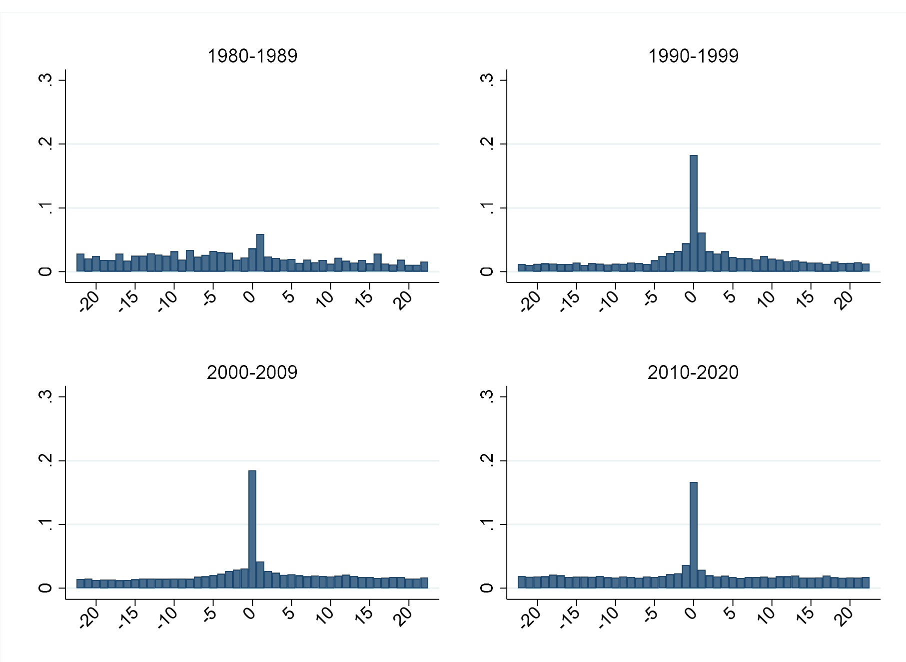


Table 1. Addition and Deletion Returns by year.

Announcement returns (Ann.) are the returns from the day before to the day after the announcement. Effective returns (Eff.) are the returns from the day before to the day after the index change became effective. Total returns are the returns from the day before the announcement to the day after the index change became effective. The table reports means by year, as well as the median for the total return. All returns are market-adjusted.

	Additions					Deletions				
		Mean			Median		Mean			Median
Year	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**
1980	5	5.90%	5.90%	5.90%	3.84%	0	-	-	-	-
1981	15	3.76%	3.76%	3.76%	3.53%	2	-1.25%	-1.25%	-1.25%	-1.25%
1982	22	3.03%	3.03%	3.03%	2.44%	4	-3.42%	-3.42%	-3.42%	-3.82%
1983	8	3.10%	3.10%	3.10%	2.51%	6	-2.75%	-2.75%	-2.75%	-2.71%
1984	28	1.75%	1.75%	1.75%	1.64%	3	-8.38%	-8.38%	-8.38%	-6.11%
1985	26	2.04%	2.04%	2.04%	1.70%	2	-30.39%	-30.39%	-30.39%	-30.39%
1986	23	4.28%	4.28%	4.28%	3.69%	3	8.73%	8.73%	8.73%	2.05%
1987	21	6.14%	6.14%	6.14%	6.98%	2	-3.91%	-3.91%	-3.91%	-3.91%
1988	20	3.71%	3.71%	3.71%	5.02%	5	-3.66%	-3.66%	-3.66%	0.11%
1989	28	2.79%	3.33%	3.18%	3.36%	12	-5.41%	-5.24%	-5.19%	0.30%
1990	7	3.34%	1.83%	5.27%	6.92%	2	-54.61%	-31.22%	-39.83%	-39.83%
1991	8	8.72%	5.60%	8.96%	8.03%	4	-50.74%	-31.50%	-36.87%	-38.19%
1992	5	4.55%	3.35%	8.04%	4.55%	5	-24.24%	-19.26%	-37.07%	-25.58%
1993	7	4.80%	4.72%	7.29%	8.36%	3	-0.79%	-4.76%	-8.90%	-3.54%
1994	7	3.39%	1.02%	3.98%	5.69%	6	-4.66%	0.27%	-8.12%	-8.47%
1995	11	2.65%	2.57%	5.85%	6.75%	10	-5.91%	-7.51%	-14.17%	-13.11%
1996	16	4.67%	2.90%	7.88%	5.10%	7	-5.55%	-1.84%	-8.17%	-5.68%
1997	13	7.63%	5.77%	11.09%	10.91%	3	-8.32%	-1.23%	-8.93%	-8.88%
1998	24	5.26%	4.92%	9.13%	7.85%	6	-10.92%	-1.41%	-9.42%	-8.11%
1999	30	5.21%	2.96%	6.32%	7.34%	5	-16.78%	-8.64%	-15.09%	-4.50%
2000	37	7.18%	2.74%	9.42%	5.16%	17	-13.83%	-5.12%	-16.71%	-15.16%

Table 1. [Continued]

Year	Additions					Deletions				
		Mean			Median		Mean			Median
	# Obs	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**
2001	22	3.78%	0.09%	5.49%	1.64%	6	-8.81%	-5.09%	-11.27%	-7.02%
2002	15	3.72%	2.00%	6.50%	4.17%	11	-9.08%	-3.99%	-11.50%	-7.35%
2003	7	2.54%	-0.16%	0.75%	1.61%	3	-23.94%	-2.52%	-24.18%	-21.28%
2004	12	2.73%	2.01%	4.76%	3.62%	6	-3.14%	-0.92%	-4.67%	-5.14%
2005	12	3.64%	0.93%	3.65%	3.24%	2	-4.56%	-2.62%	-7.53%	-7.53%
2006	22	4.40%	1.77%	5.89%	6.08%	7	-5.33%	-1.09%	-6.86%	-6.06%
2007	30	2.39%	1.59%	2.73%	2.41%	4	2.41%	-0.10%	0.65%	0.21%
2008	30	4.71%	1.43%	5.56%	5.92%	14	-20.64%	-10.26%	-23.98%	-16.40%
2009	23	2.52%	-0.84%	1.84%	1.16%	16	-4.02%	-2.60%	-5.24%	-4.01%
2010	14	1.99%	-1.05%	-0.47%	0.22%	3	0.74%	4.34%	5.77%	-0.68%
2011	8	0.17%	-1.00%	-1.87%	-0.76%	9	1.03%	0.25%	-1.78%	-1.24%
2012	5	4.61%	-1.33%	3.11%	2.79%	5	-1.71%	-2.58%	-4.19%	-7.76%
2013	11	2.45%	1.54%	3.01%	2.99%	10	-1.40%	2.95%	0.76%	0.15%
2014	8	1.79%	0.07%	0.68%	0.08%	8	2.71%	-0.62%	2.71%	3.50%
2015	19	2.08%	0.46%	2.56%	1.98%	6	-2.04%	-1.69%	0.47%	0.68%
2016	21	0.24%	-1.06%	-0.53%	-1.02%	7	4.18%	1.67%	6.31%	2.84%
2017	19	0.47%	0.18%	-0.26%	-0.57%	11	1.35%	-0.80%	-0.40%	0.95%
2018	21	0.09%	0.67%	-1.04%	-2.61%	8	-0.28%	0.44%	-2.09%	1.92%
2019	12	0.28%	0.95%	0.90%	-0.88%	10	-6.87%	0.18%	-6.09%	0.11%
2020	12	0.40%	2.31%	5.49%	0.64%	10	1.11%	-0.77%	-2.70%	-3.33%

Table 2. Addition and Deletion Returns by decade.

In each 10-year period, we run a regression of the individual total, announcement and implementation return on a constant term. Announcement returns are the returns from the day before to the day after the announcement. Effective returns are the returns from the day before to the day after the index change became effective. Total returns are the returns from the day before the announcement to the day after the index change became effective. The last column shows the difference between the 2010-2020 period and the 2000-2009 period. Robust standard errors in parenthesis.

Panel A: Additions

	All	**1980-1989**	**1990-1999**	**2000-2009**	**2010-2020**	**(2010-2020) - (2000-2009)**
Total	0.0417***	0.0342***	0.0759***	0.0521***	0.00799	-0.044***
	(0.003)	(0.003)	(0.008)	(0.007)	(0.006)	(0.009)
Announcement	0.0342***	0.0336***	0.0515***	0.0413***	0.0105***	-0.031***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Effective	0.0213***	0.0344***	0.0368***	0.0132***	0.00209	-0.011**
	(0.002)	(0.003)	(0.005)	(0.004)	(0.002)	(0.005)
Observations	684	196	128	210	150	N/A

Panel B: Deletions

	All	**1980-1989**	**1990-1999**	**2000-2009**	**2010-2020**	**(2010-2020) - (2000-2009)**
Total	-0.0813***	-0.0464**	-0.166***	-0.123***	-0.00603	0.117***
	(0.011)	(0.018)	(0.023)	(0.023)	(0.011)	(0.026)
Announcement	-0.0687***	-0.0471**	-0.144***	-0.101***	-0.002	0.099***
	(0.010)	(0.018)	(0.029)	(0.021)	(0.009)	(0.023)
Effective	-0.0372***	-0.0465**	-0.0864***	-0.0434**	0.002	0.045**
	(0.008)	(0.018)	(0.021)	(0.019)	(0.006)	(0.019)
Observations	263	39	51	86	87	N/A

Table 3. Abnormal returns, controlling for characteristics.

We estimate the following multivariate regression separately for additions and deletions:

$$Total\ Return_{it} = b_1 turnover_{i,t-1} + b_2\ size_{i,t-1} + b_3 volatility_{i,t-1} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it}$$

Where $Total\ Return_{it}$ is the cumulative return from the day before the announcement to the day after the implementation, and measured in percent. $turnover_{i,t-1}$ is the average turnover (defined as volume divided by shares outstanding) in stock *i* over the month before the index change, minus the value-weighted average turnover across all ordinary common shares traded on major exchanges in CRSP over the same period. $size_{i,t-1}$ is the firm's market capitalization on the last day before the announcement of the index change relative to the total market capitalization of the S&P 500 on the same day. $volatility_{i,t-1}$ is the sum of daily squared percentage market-adjusted stock returns the month before index addition or deletion. $1_{era=k}$ are dummy variables for 10-year periods. Robust standard errors in parenthesis. The rows labeled e.g., 2010s vs. 1980s are the differences in the coefficients between these two eras. F-statistics from a test on equality of these coefficients reported in parenthesis.

	Additions		Deletions	
	(1)	(2)	(3)	(4)
Turnover $_{t-1}$		0.242		-0.959
		(0.52)		(1.06)
% of S&P Cap.		18.00***		29.93***
		(4.78)		(11.23)
Stock Volatility $_{t-1}$		0.167**		-0.083
		(0.08)		(0.05)
1980-1989	3.457***	1.324**	-4.635**	-3.941
	(0.28)	(0.56)	(1.83)	(2.48)
1990-1999	7.586***	4.713***	-16.58***	-15.51***
	(0.81)	(1.03)	(2.29)	(2.28)
2000-2009	5.208***	2.116***	-12.31***	-9.352***
	(0.69)	(0.68)	(2.31)	(1.74)
2010-2020	0.799	-1.653***	-0.603	1.613
	(0.56)	(0.59)	(1.12)	(2.36)
Observations	678	678	263	263
R-squared	0.272	0.348	0.295	0.378
2010s vs. 1980s	-2.659	-2.977	4.033	5.554
	(18.06)	(34.30)	(3.55)	(3.83)
2010s vs. 1990s	-6.788	-6.366	15.98	17.12
	(47.96)	(47.04)	(39.34)	(30.22)
2010s vs. 2000s	-4.409	-3.769	11.71	10.97
	(24.78)	(26.76)	(20.74)	(17.65)

Table 4. Cumulative pre-announcement returns.

In each 10-year period, we run a regression of the cumulative returns from t=n to t=-1 relative to the announcement, where n is either -100, -50, -20 or -10. Robust standard errors in parenthesis.

	Window	1980-1989	1990-1999	2000-2009	2010-2020
Additions	-100,-1	0.069	0.103	0.141	0.193
		(0.014)	(0.031)	(0.022)	(0.030)
	-50,-1	0.027	0.032	0.058	0.072
		(0.009)	(0.013)	(0.013)	(0.011)
	-20,-1	0.008	0.022	0.020	0.025
		(0.006)	(0.009)	(0.009)	(0.007)
	-10,-1	0.004	0.013	0.013	0.010
		(0.004)	(0.007)	(0.006)	(0.004)
Deletions	-100,-1	-0.028	-0.172	-0.201	-0.224
		(0.067)	(0.049)	(0.037)	(0.021)
	-50,-1	-0.015	-0.111	-0.187	-0.117
		(0.059)	(0.039)	(0.031)	(0.019)
	-20,-1	-0.055	-0.054	-0.129	-0.030
		(0.041)	(0.037)	(0.025)	(0.014)
	-10,-1	-0.026	-0.048	-0.103	-0.019
		(0.035)	(0.031)	(0.020)	(0.011)

Table 5. Index effect decomposition.

Estimates of liquidity based on

$$\overline{Price\ Impact} = M \times (w \cdot \bar{D}_{Migrations} + (1-w) \cdot \bar{D}_{NonMigrations})$$

Price impact is measured as the cumulative market-adjusted return from the day before the announcement to the day after the implementation. D (migrations) is the net demand by index index trackers minus the percentage of the S&P 400 MidCap owned by tracking funds, expressed as a percentage of shares outstanding. D(non-migrations) is the net purchases by index trackers. M is estimated by dividing the average abnormal return by the weighted mean of D. ε is the demand elasticity, equal to minus one divided by M. We estimate this separately for additions and deletions and by era.

	N events	Average abnormal return (%)	D (Migrations)	D (Non-Migrations)	w=% Migrations	D	M	ε = -1/M
				Additions				
1995-1999	94	7.91	1.11	1.23	44.68%	1.18	6.71	-0.15
2000-2009	210	5.21	0.67	2.45	38.10%	1.78	2.93	-0.34
2010-2020	150	0.80	-0.45	4.86	40.67%	2.70	0.30	-3.39
				Deletions				
1995-1999	31	-11.54	-0.95	-1.07	6.45%	-1.06	10.84	-0.09
2000-2009	86	-12.31	-0.65	-2.43	6.98%	-2.30	5.35	-0.19
2010-2020	87	-0.60	0.36	-4.95	58.62%	-1.84	0.33	-3.05

Table 6. Net buying and selling by trackers and institutional investors.

Net buying and selling by trackers are defined as in Figure 1. Net buying and selling by institutions (Insts.) are defined as the total change in split-adjusted shares held by 13F filing institutions between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding. Net buying by active and passive mutual funds is defined similarly. We compute the median of this quantity among additions and deletions each year. The final row represents an equal weighted average across the yearly medians.

	Additions				Deletions			
Year	Trackers	Passive	Active	Insts.	Trackers	Passive	Active	Insts.
1980	0.01%	0.01%	0.41%	-0.18%	-	-	-	-
1981	0.01%	0.01%	-0.03%	0.91%	-0.01%	-0.01%	0.54%	-0.08%
1982	0.01%	0.01%	0.35%	3.40%	-0.01%	-0.01%	0.18%	-3.07%
1983	0.02%	0.02%	0.11%	0.54%	-0.02%	-0.02%	-0.48%	0.47%
1984	0.02%	0.02%	-0.14%	2.43%	-0.01%	-0.01%	-0.09%	0.24%
1985	0.03%	0.03%	-0.25%	2.48%	-0.01%	-0.01%	-4.65%	-10.14%
1986	0.03%	0.03%	0.48%	3.51%	-0.02%	-0.02%	-2.52%	-21.12%
1987	0.05%	0.05%	0.14%	1.37%	-0.05%	-0.05%	3.75%	-4.12%
1988	0.06%	0.05%	0.42%	3.24%	-0.06%	-0.05%	-8.49%	-36.75%
1989	0.10%	0.07%	0.08%	2.22%	-0.07%	-0.06%	-2.35%	-18.13%
1990	0.15%	0.10%	1.17%	0.54%	-0.23%	0.00%	-5.07%	-23.99%
1991	0.22%	0.19%	0.26%	1.58%	-0.12%	-0.11%	-1.11%	-5.76%
1992	0.26%	0.23%	0.26%	0.97%	-0.16%	-0.14%	-0.09%	-4.22%
1993	0.49%	0.34%	0.21%	1.68%	-0.41%	-0.34%	-0.49%	-1.18%
1994	0.56%	0.41%	-0.55%	0.77%	-0.66%	-0.40%	-0.01%	-3.97%
1995	0.66%	0.51%	1.00%	3.23%	-0.69%	-0.41%	0.76%	-3.02%
1996	1.10%	0.95%	-0.66%	0.27%	-1.00%	-0.74%	1.40%	-1.56%
1997	1.35%	1.14%	0.83%	0.33%	-1.28%	-0.76%	0.28%	1.88%
1998	1.46%	1.34%	0.23%	0.87%	-1.36%	-1.02%	-4.32%	-1.74%
1999	1.59%	1.49%	-1.01%	0.28%	-1.45%	-1.21%	-1.44%	-0.42%
2000	1.60%	1.58%	2.19%	1.36%	-1.55%	-0.80%	-2.29%	-3.47%
2001	1.08%	1.05%	-0.79%	0.42%	-0.91%	-0.03%	-0.29%	1.81%
2002	1.34%	1.22%	-0.26%	-0.06%	-1.15%	-1.23%	-0.14%	-2.00%
2003	2.15%	1.70%	-1.85%	-1.09%	-2.01%	-1.82%	-1.93%	3.69%
2004	2.42%	1.49%	-0.73%	0.93%	-2.33%	-1.23%	0.25%	0.52%
2005	2.70%	1.43%	-0.74%	-0.20%	-3.29%	-3.17%	0.83%	-2.01%
2006	2.63%	1.82%	-0.05%	0.36%	-3.00%	-1.85%	-0.54%	-3.20%
2007	2.80%	1.76%	0.53%	0.45%	-2.88%	-1.04%	2.62%	-1.94%
2008	3.84%	2.05%	1.06%	1.46%	-3.50%	-2.46%	-7.65%	-7.35%
2009	3.75%	1.75%	0.13%	0.42%	-4.09%	-3.20%	-1.78%	-2.82%
2010	3.84%	1.46%	0.50%	0.61%	-4.28%	-1.09%	0.90%	3.56%
2011	4.11%	0.79%	1.11%	0.30%	-4.51%	-0.92%	-0.93%	-0.25%
2012	4.28%	2.65%	-4.49%	0.73%	0.00%	0.33%	2.19%	-0.07%
2013	4.68%	1.25%	0.09%	1.86%	-4.78%	-1.28%	0.71%	0.45%
2014	4.97%	1.31%	0.07%	2.49%	-5.34%	-1.41%	1.89%	2.64%
2015	5.33%	2.12%	0.19%	1.11%	-6.32%	-3.00%	-3.47%	-4.16%
2016	5.97%	1.16%	0.41%	0.59%	-6.55%	-1.75%	-0.87%	-2.97%
2017	5.18%	0.43%	-0.10%	0.47%	-6.88%	-1.94%	-0.77%	0.32%
2018	6.81%	3.66%	0.35%	0.61%	-5.78%	0.15%	-1.52%	-1.62%
2019	6.04%	0.94%	-0.49%	0.36%	-7.57%	-2.37%	-4.75%	-6.40%
2020	6.85%	2.72%	10.48%	-0.66%	-7.47%	-2.29%	7.26%	-0.75%
Average	2.91%	1.32%	0.30%	0.74%	-2.95%	-1.21%	-0.66%	-2.26%

Figure A1. Alternative method of identifying S&P 500 trackers.

Each year, we identify S&P 500 index funds based on names and objective codes. To identify funds based on objective codes we use CRSP objective codes SP and SPSP. To identify funds based on names we use variants of "S&P 500", "S and P 500" and "SP 500". Finally, we add up the total assets of these funds, and divide them by the total market capitalization of the S&P 500 index.

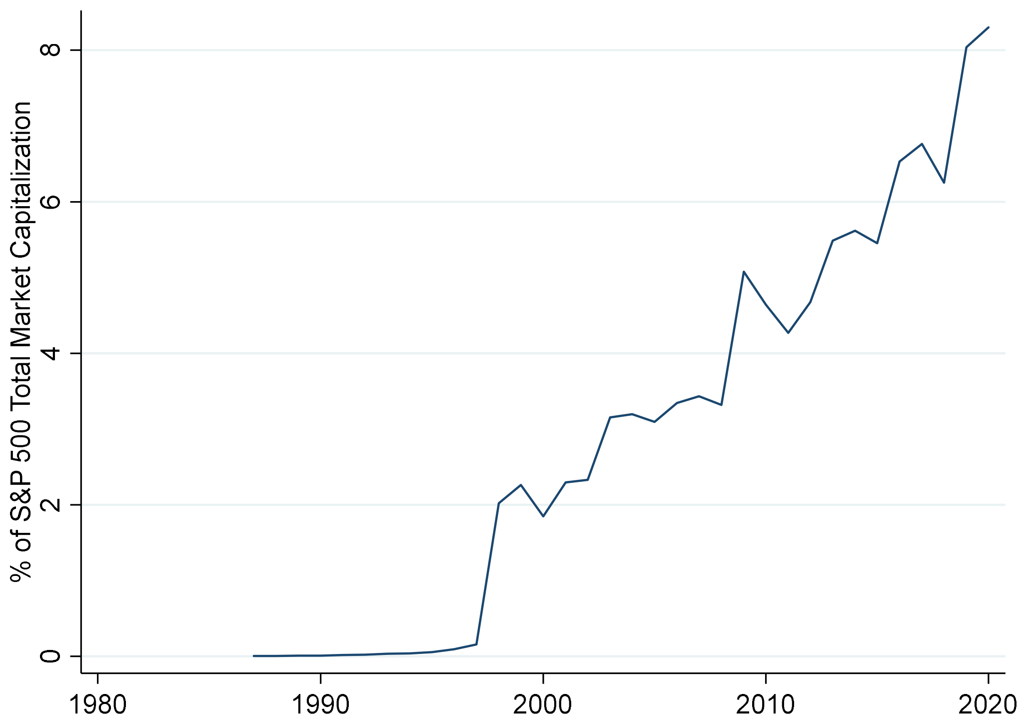


Table A1. Sample selection

Each year, we report the total number of S&P 500 index additions and deletions that can be matched from Siblis to CRSP. We also report the number of firms in our final sample, which excludes those that are listed, acquired, delisted for reasons other than acquisition, or are acquirers within 100 days of the index change. Our filters also exclude firms which cannot be matched to the Thompson S12 data in either the quarter before or after the index change or have missing returns around the time of the index change announcement or implementation.

Year	Total Drops	Drops Sample	% Included	Total Adds	Adds Sample	% Included
1980	-	-	-	11	5	45%
1981	3	2	67%	21	15	71%
1982	13	4	31%	27	22	81%
1983	11	6	55%	11	8	73%
1984	12	3	25%	30	28	93%
1985	11	2	18%	28	26	93%
1986	16	3	19%	28	23	82%
1987	13	2	15%	25	21	84%
1988	22	5	23%	25	20	80%
1989	27	12	44%	29	28	97%
1990	12	2	17%	12	7	58%
1991	12	4	33%	12	8	67%
1992	7	5	71%	7	5	71%
1993	10	3	30%	11	7	64%
1994	17	6	35%	17	7	41%
1995	29	10	34%	28	11	39%
1996	22	7	32%	22	16	73%
1997	26	3	12%	26	13	50%
1998	40	6	15%	40	24	60%
1999	41	5	12%	39	30	77%
2000	55	17	31%	56	37	66%
2001	30	6	20%	30	22	73%
2002	23	11	48%	23	15	65%
2003	8	3	38%	9	7	78%
2004	19	6	32%	18	12	67%
2005	18	2	11%	17	12	71%
2006	30	7	23%	30	22	73%
2007	38	4	11%	38	30	79%
2008	37	14	38%	37	30	81%
2009	26	16	62%	26	23	88%
2010	16	3	19%	16	14	88%
2011	20	9	45%	20	8	40%
2012	17	5	29%	17	5	29%
2013	19	10	53%	19	11	58%
2014	14	8	57%	16	8	50%
2015	24	6	25%	27	19	70%
2016	28	7	25%	28	21	75%
2017	27	11	41%	26	19	73%
2018	23	8	35%	24	21	88%
2019	21	10	48%	21	12	57%
2020	16	10	63%	16	12	75%
Average	23	7	34%	23	16	66%

Table A2. Sensitivity of returns to sample selection.

Our sample excludes firms that are listed, acquired, delisted for reasons other than acquisition, or are acquirers within 100 days of the index change. We also exclude firms that cannot be matched to the Thompson S12 data in either the quarter before or after the index change or have missing returns around the time of the index change announcement or implementation. Announcement returns (Ann.) are the returns from the day before to the day after the announcement. Effective returns (Eff.) are the returns from the day before to the day after the index change became effective. Total returns are the returns from the day before the announcement to the day after the index change became effective. Returns are market-adjusted.

	Adds								Drops							
	Our Sample (requires S12)				Full Sample				Our Sample (requires S12)				Full Sample			
Year	# Obs.	Ann.	Eff.	Total	# Obs.	Ann.	Eff.	Total	# Obs.	Ann.	Eff.	Total	# Obs.	Ann.	Eff.	Total
1980	5	5.90%	5.90%	5.90%	11	4.27%	4.27%	4.27%	-	-	-	-	-	-	-	-
1981	15	3.76%	3.76%	3.76%	21	3.26%	3.26%	3.26%	2	-1.25%	-1.25%	-1.25%	3	-3.51%	-3.51%	-3.51%
1982	22	3.03%	3.03%	3.03%	27	2.60%	2.60%	2.60%	4	-3.42%	-3.42%	-3.42%	13	-2.06%	-2.06%	-2.06%
1983	8	3.10%	3.10%	3.10%	11	3.07%	3.07%	3.07%	6	-2.75%	-2.75%	-2.75%	11	-2.08%	-2.08%	-2.08%
1984	28	1.75%	1.75%	1.75%	30	1.72%	1.72%	1.72%	3	-8.38%	-8.38%	-8.38%	12	-2.73%	-2.73%	-2.73%
1985	26	2.04%	2.04%	2.04%	28	1.92%	1.92%	1.92%	2	-30.39%	-30.39%	-30.39%	11	-5.83%	-5.83%	-5.83%
1986	23	4.28%	4.28%	4.28%	28	4.02%	4.02%	4.02%	3	8.73%	8.73%	8.73%	16	1.51%	1.51%	1.51%
1987	21	6.14%	6.14%	6.14%	25	5.65%	5.65%	5.65%	2	-3.91%	-3.91%	-3.91%	13	-1.26%	-1.26%	-1.26%
1988	20	3.71%	3.71%	3.71%	25	3.75%	3.75%	3.75%	5	-3.66%	-3.66%	-3.66%	22	-1.85%	-1.85%	-1.85%
1989	28	2.79%	3.33%	3.18%	29	2.76%	3.28%	3.14%	12	-5.41%	-5.24%	-5.19%	27	-2.27%	-2.23%	-2.52%
1990	7	3.34%	1.83%	5.27%	12	1.98%	1.56%	3.58%	2	-54.61%	-31.22%	-39.83%	12	-7.55%	-3.86%	-4.84%
1993	8	8.72%	5.60%	8.96%	12	5.66%	5.66%	7.07%	4	-50.74%	-31.50%	-36.87%	12	-16.17%	-11.26%	-11.56%
1994	7	3.39%	1.02%	3.98%	17	1.92%	0.64%	3.14%	6	-4.66%	0.27%	-8.12%	17	-1.41%	0.77%	-1.97%
1995	11	2.65%	2.57%	5.85%	28	3.30%	2.34%	4.58%	10	-5.91%	-7.51%	-14.17%	29	-2.21%	-2.18%	-4.80%
1996	16	4.67%	2.90%	7.88%	22	4.39%	2.25%	6.60%	7	-5.55%	-1.84%	-8.17%	22	-2.40%	-0.15%	-2.09%
1997	13	7.63%	5.77%	11.09%	26	5.87%	3.99%	7.40%	3	-8.32%	-1.23%	-8.93%	26	-0.49%	-0.03%	-0.66%
1998	24	5.26%	4.92%	9.13%	40	4.83%	2.46%	6.54%	6	-10.92%	-1.41%	-9.42%	40	-1.01%	-1.08%	-1.07%
1999	30	5.21%	2.96%	6.32%	39	5.01%	3.31%	7.47%	5	-16.78%	-8.64%	-15.09%	41	-0.91%	-1.14%	-0.61%
2000	37	7.18%	2.74%	9.42%	56	5.90%	1.94%	8.75%	17	-13.83%	-5.12%	-16.71%	55	-3.83%	-1.96%	-4.94%
2001	22	3.78%	0.09%	5.49%	30	2.74%	-0.08%	3.77%	6	-8.81%	-5.09%	-11.27%	30	-7.01%	-2.43%	-6.02%
2002	15	3.72%	2.00%	6.50%	23	3.82%	1.65%	5.37%	11	-9.08%	-3.99%	-11.50%	23	-9.73%	-5.79%	-10.76%
2003	7	2.54%	-0.16%	0.75%	9	2.38%	0.63%	1.34%	3	-23.94%	-2.52%	-24.18%	8	-8.23%	0.31%	-7.62%
2004	12	2.73%	2.01%	4.76%	18	1.24%	1.09%	3.24%	6	-3.14%	-0.92%	-4.67%	19	-0.20%	-0.52%	-0.30%
2005	12	3.64%	0.93%	3.65%	17	3.02%	1.23%	3.69%	2	-4.56%	-2.62%	-7.53%	18	-8.38%	-8.73%	-11.06%
2006	22	4.40%	1.77%	5.89%	30	3.94%	0.56%	3.80%	7	-5.33%	-1.09%	-6.86%	30	-2.00%	-2.22%	-3.70%
2007	30	2.39%	1.59%	2.73%	38	2.11%	0.90%	2.04%	4	2.41%	-0.10%	0.65%	38	0.30%	0.59%	0.85%
2008	30	4.71%	1.43%	5.56%	37	4.41%	1.92%	5.51%	14	-20.64%	-10.26%	-23.98%	37	-9.77%	-6.58%	-11.58%
2009	23	2.52%	-0.84%	1.84%	26	2.96%	-0.94%	1.69%	16	-4.02%	-2.60%	-5.24%	26	-4.64%	-2.30%	-6.33%
2010	14	1.99%	-1.05%	-0.47%	16	1.95%	-0.81%	-0.34%	3	0.74%	4.34%	5.77%	16	-0.57%	0.02%	-0.11%
2011	8	0.17%	-1.00%	-1.87%	20	0.47%	-0.87%	-0.22%	9	1.03%	0.25%	-1.78%	20	0.39%	0.64%	-0.38%
2012	5	4.61%	-1.33%	3.11%	17	2.43%	-0.76%	1.19%	5	-1.71%	-2.58%	-4.19%	17	-0.85%	-1.42%	-1.74%
2013	11	2.45%	1.54%	3.01%	19	2.08%	1.05%	2.23%	10	-1.40%	2.95%	0.76%	19	-0.25%	1.35%	0.53%
2014	8	1.79%	0.07%	0.68%	16	2.36%	-0.43%	0.78%	8	2.71%	-0.62%	2.71%	14	1.89%	-0.20%	1.78%
2015	19	2.08%	0.46%	2.56%	27	1.10%	0.23%	1.57%	6	-2.04%	-1.69%	0.46%	24	-1.49%	0.03%	-0.15%
2016	21	0.24%	-1.06%	-0.53%	28	0.89%	-1.26%	-0.05%	7	4.18%	1.67%	6.31%	28	1.95%	-0.55%	1.85%
2017	19	0.47%	0.18%	-0.26%	26	0.57%	-0.40%	-0.21%	11	1.35%	-0.80%	-0.40%	27	1.12%	-1.36%	-0.33%
2018	21	0.09%	0.67%	-1.04%	24	0.06%	0.51%	-1.16%	8	-0.28%	0.44%	-2.09%	23	0.19%	0.46%	-0.28%
2019	12	0.28%	0.95%	0.90%	21	-0.51%	1.40%	0.51%	10	-6.87%	0.18%	-6.09%	21	-3.68%	-0.30%	-3.79%
2020	12	0.40%	2.31%	5.49%	16	-1.49%	-0.29%	2.04%	10	1.11%	-0.77%	-2.70%	16	0.75%	-0.37%	-1.90%